Prognostics for Batteries

Aging Experiments and Modeling

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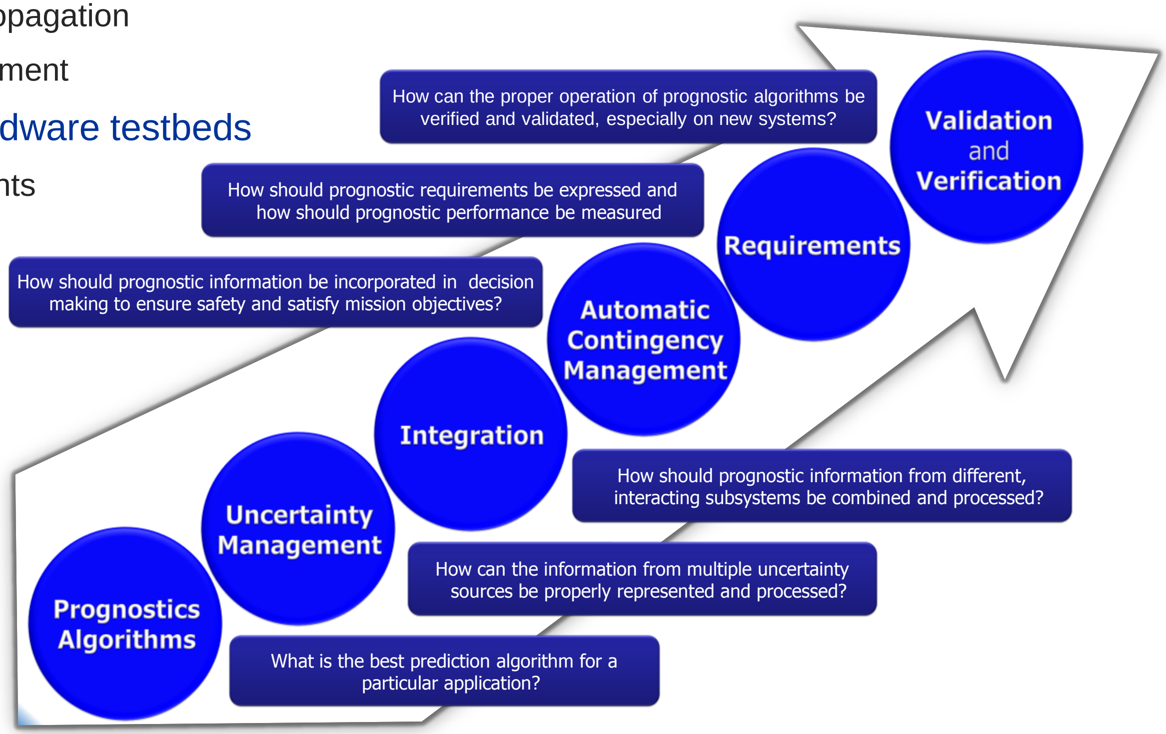
Prognostics Center of Excellence

NASA Ames Research Center, CA

Mission: Advance state-of-the-art in prognostics technology development

- Investigate algorithms for estimation of remaining life
  - Investigate physics-of-failure
  - Model damage initiation and propagation
  - Investigate uncertainty management
- Validate research findings in hardware testbeds
  - Hardware-in-the-loop experiments
  - Accelerated aging testbeds
  - HIL demonstration platforms
- Systems Engineering Aspects
  - SE process
  - Requirements
  - V&V
  - Certification
- Disseminate research findings
  - Public data repository for run-to-failure data
  - Actively publish research results
- Engage research community



Prognostics CoE

- Prognostics Center of Excellence, NASA Ames Research Center, CA [http://www.prognostics.nasa.gov]

Outline

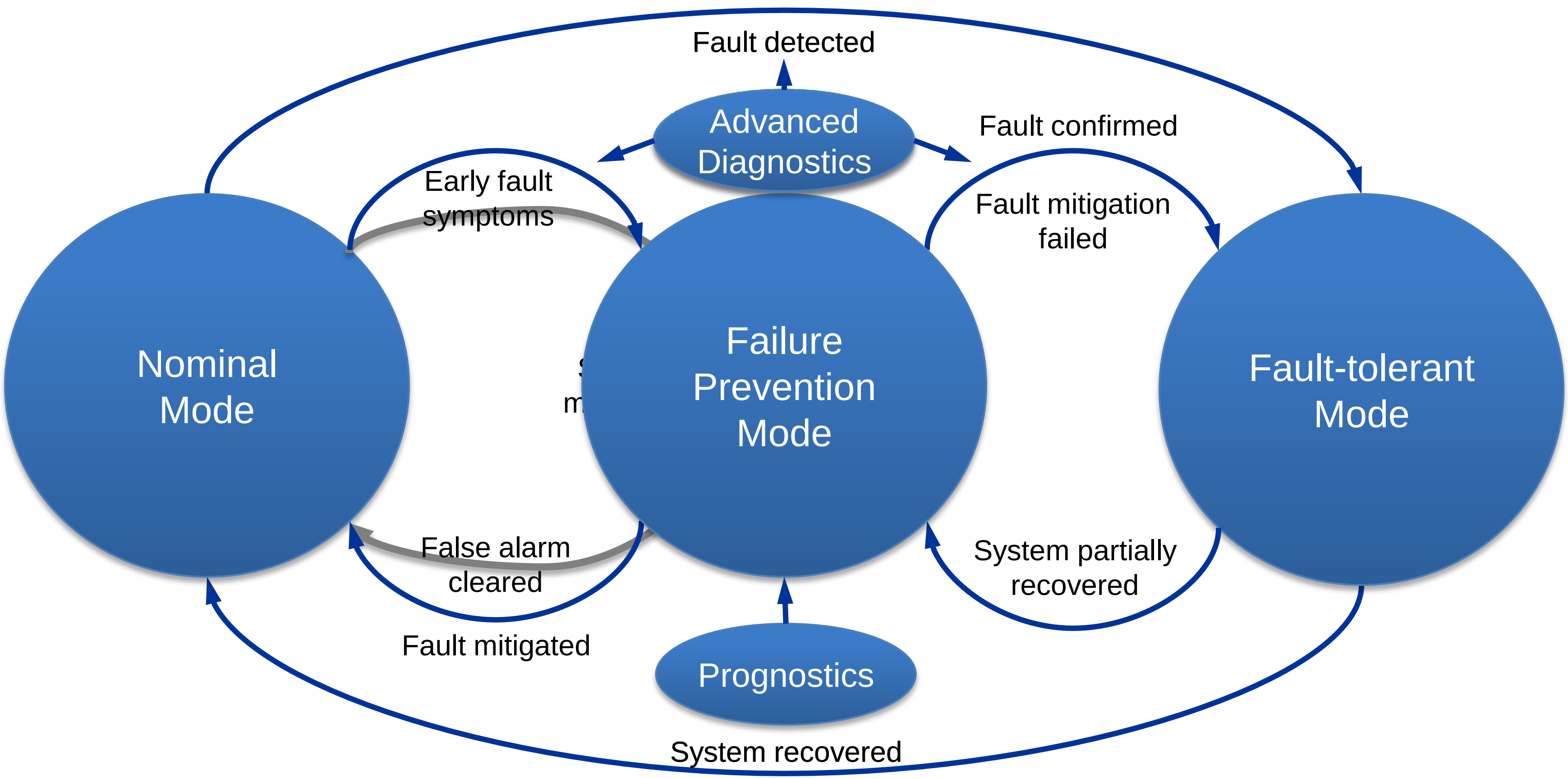
1. Prognostics and its use for battery applications
2. Battery modeling and validation for prognostics
3. Aging and fault injection experiments

Prognostics

- An element of systems health management
  - Detection, Diagnosis, Prognosis, Mitigation
- Definition
  - "***Predicting*** *time at which a component will no longer perform its intended function within desired specification*"
    - Time at which this happens is called **End-of-Life** (EOL)
    - Lack of functional performance is often defined as component failure
      - Due to a fault condition
      - Due to wear and degradation
    - Predicted time becomes **Remaining Useful Life** (RUL)
- Predictions are based on
  - Analysis of failure modes
  - Detection of early signs of wear and aging, and fault conditions
  - Correlation of signs of aging with a mathematical description of how the damage is expected to increase
    - The *damage propagation model*
  - Condition monitoring data
  - Expected future loading

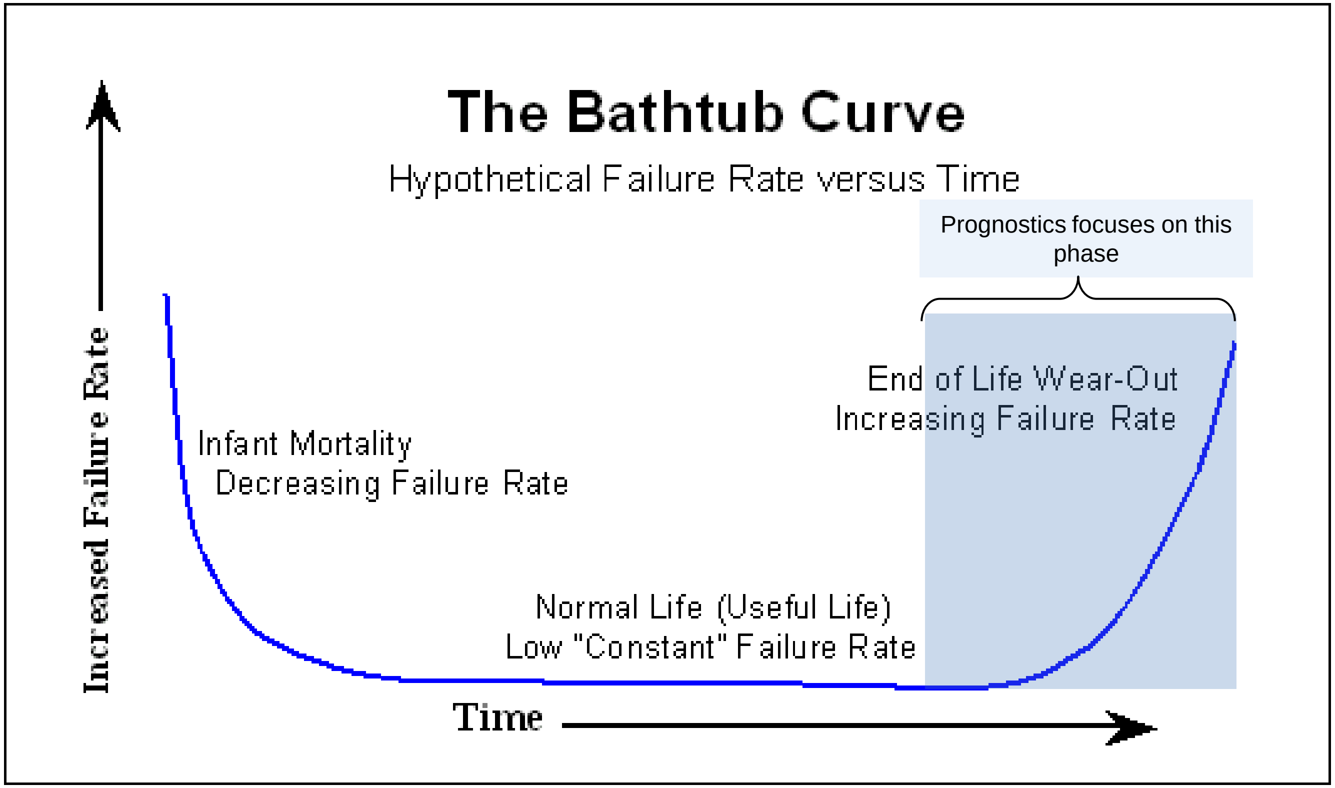
Source: http://prognostics.nasa.gov

Paradigm Change in Health Management



Moving from Scheduled or Reactive Maintenance to Condition-Based Maintenance (CBM)

Aren’t we talking Battery Reliability?



An aggregate statistical measure like **Failure Rate** (# of failures/population size) must NOT be confused with the true **Remaining Useful Life** (RUL) distribution of a specific unit

Concept Similarities and Differences

- MTBF
  - A common term used in specifying and marketing products is MTBF, which is a vastly misunderstood (and often misused) term. MTBF historically stands for "Mean Time Between Failures," and as such, applies only when the underlying distribution has a constant failure rate (*e.g.* an exponential distribution).

Dennis J. Wilkins, Retired Hewlett-Packard Senior Reliability Specialist, currently a ReliaSoft Reliability Field Consultant, "*The Bathtub Curve and Product Failure Behavior*", Reliability Hotwire, Issue 22, December 2002

- RUL
  - We define RUL as amount of time left before system health falls below a defined failure threshold, based on the current state assessment and expected future operational conditions of the system.

A. Saxena, J. Celaya, E. Balaban, K. Goebel, B. Saha, S Saha, and M. Schwabacher, "Metrics for Evaluating Performance of Prognostic Techniques", *Intl. Conf. on Prognostics and Health Management*, Denver, CO, October 2008.

Source: http://prognostics.nasa.gov

Benefits of Prognostics

- Paradigm Switch
  - From reactive troubleshooting to proactive failure avoidance
    - ***Predict*** when failure will occur with high confidence
    - Provide optimized ***actionable decision*** support
  - Information on
    - Time-to-criticality
    - Degree of wear/degradation
- Benefits
  - Increase mission/launch availability
  - Provide informed decision when to continue/cancel operation
  - Avoid unscheduled maintenance
  - Facilitate risk reduction
  - Support go/no-go decisions
  - Enable design improvement
  - Assist with cost reduction

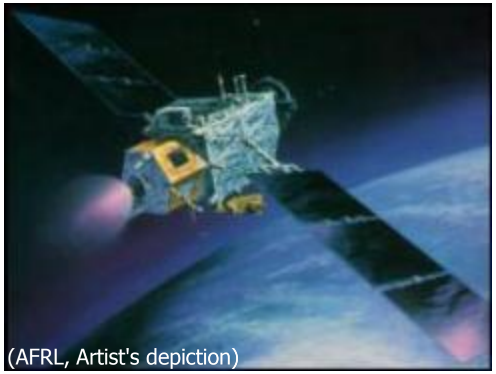
Source: http://prognostics.nasa.gov

What is BMS?

- BMS - Battery Monitoring System
- Battery Health **Monitoring**
  - Keep a continuous track of battery health
    - May not need internal battery information but needs continuous monitoring of key variables
    - Use information to Make decisions for a system that depends on battery power – i.e. based on what a system can or cannot do
- Battery Health **Management**
  - Make decisions to optimize battery usage to extend battery life
    - Decisions at the system level – choose to alter system operational profile to selectively reduce load on aging batteries
    - Decisions at the battery level – make internal adjustments to a battery to let alone an aging cell or pack
  - May impose design changes to way batteries are wired internally

Motivation

Electric Propulsion Space Experiment (AFRL)


(AFRL, Artist's depiction)

- 30 kW Ammonia Arcjet Launched onboard the ARGOS satellite on 23rd Feb, 1999 from Vandenberg AFB, CA
- Rising battery temp.& press. due to gases released from **electrolyte decomposition resulted in a breach of the battery case**, releasing superheated gas into the flight unit

(Courtesy: AFRL-PR-ED-TR-2001-0027)

Beech A200 (Reg # N258AG)

- Plane crashed during landing on April 08, 2000 in Seattle, WA
- Pilot failed to return engine ignition/start switches from ON to OFF after starting
- Onboard generators failed to activate as the starter was engaged
- **Battery completely discharged** resulting in total electrical failure during flight with associated disabling of normal landing gear extension capability

(Courtesy: NTSB, ID #SEA00LA066)

Mars Global Surveyor


(NASA/JPL, Artist's concept)

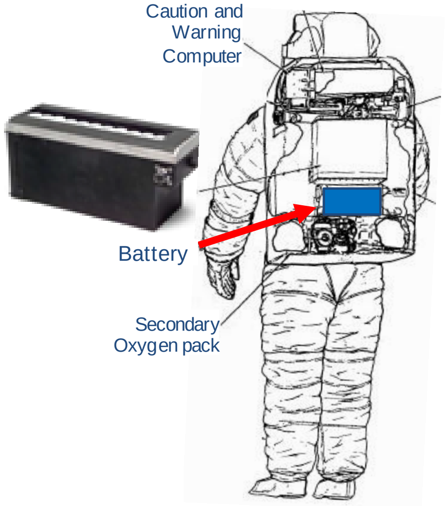
The MGS stopped operating shortly after celebrating its 10th anniversary (Nov, 2006)

"We think that the failure was due to a software load ... we drove the [solar] arrays against a hard stop and the spacecraft went into safe mode. The radiator for the battery pointed at the sun, the ***temperature went up****, and* ***battery failed****. But this should be treated as preliminary."*

John McNamee
Mars Exploration Program, NASA

Applications for Li++ Battery Prognostics

- Prediction of ***end-of-charge*** and ***end-of-life*** based on current state estimation and estimated future usage to answer
  - **Can the current mission be completed?**
    - Given the health of the battery, is there enough charge left for anticipated load profile (within allowable uncertainty bounds)?
    - Dominant metrics: state of charge (SOC), state of health (SOH)
  - **Can future missions be completed?**
    - Given the health of the battery, at what point can typical future missions not be met?
    - Dominant metrics: end of life (EOL) or remaining useful life (RUL), state of health (SOH)
  - Current target applications include both Aeronautics and Space systems:
    - Hybrid electric UAVs (Edge 540)
    - Extra Vehicular Activity (EVA) battery for astronaut suits
    - UGVs (K11 Rover)



Other Applications of BMS

- The future of transport
  - Hybrid vehicles are the face of environment friendly transportation now



- Facilitating renewable energies
  - Renewable energy sources (like solar, wind, etc.) are not continually available
  - An energy storage facility coupled with these sources would make solutions more economically viable


- Inefficiencies and wastage
  - Americans purchase nearly 3 billion batteries every year
  - In Operation Iraqi Freedom, the Marines used 3,028 batteries per day
  - A rechargeable battery can replace hundreds of single-use batteries over its life

PROGNOSTICS

Problem Formulation

- Prognostics goal
  - Compute EOL = time point at which component no longer meets specified performance criteria
  - Compute RUL = time remaining until EOL
- System model

State Parameters Input Process Noise

$$
\begin{aligned}
\dot{\mathbf{x}}(t) &= \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t)) \\
\mathbf{y}(t) &= \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t))
\end{aligned}
$$

Output Sensor Noise

- Define threshold $T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t))$ from performance specs that is 1 when system is considered failed, 0 otherwise
- EOL and RUL defined as

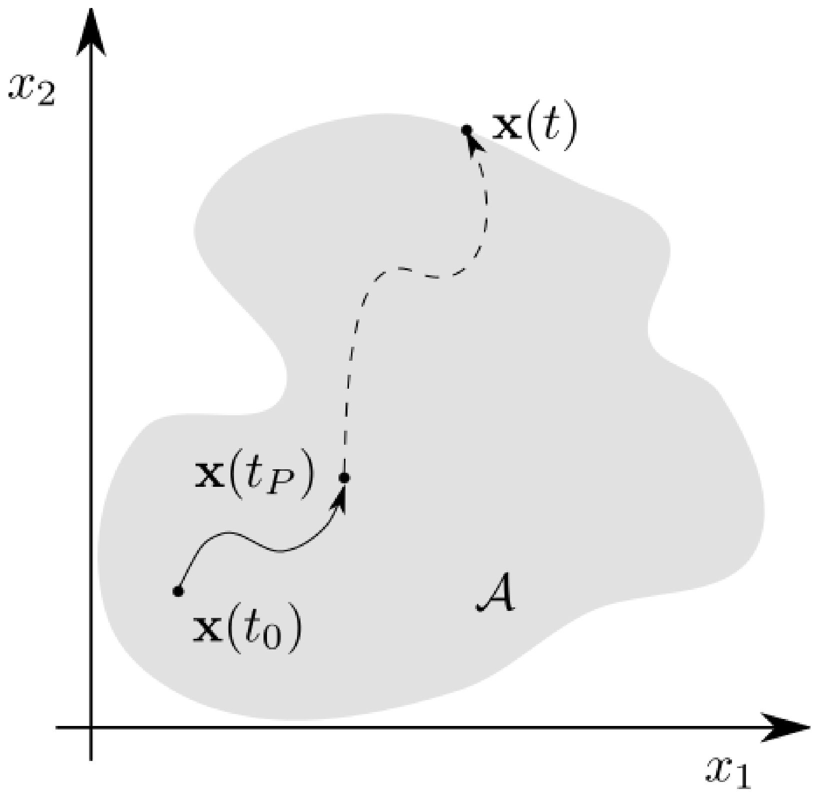
$$EOL(t_P) \triangleq \inf\{t \in \mathbb{R} : t \geq t_P \wedge T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 1\}$$

$$RUL(t_P) \triangleq EOL(t_P) - t_P$$

Compute $p(EOL(t_P)|\mathbf{y}_{0:t_P})$ and/or $p(RUL(t_P)|\mathbf{y}_{0:t_P})$

Defining EOL

- Failure threshold T_{EOL} defined with functional specifications and linked to boundary in multi-dimensional damage space
  - Beyond the boundary, the system does not conform to functional specifications (or operational risk is too great)
  - Within the boundary, the system is still functioning properly
- From time t_0 to prediction time t_P, system behaves within specs
- Interested at what time t system will exit this region

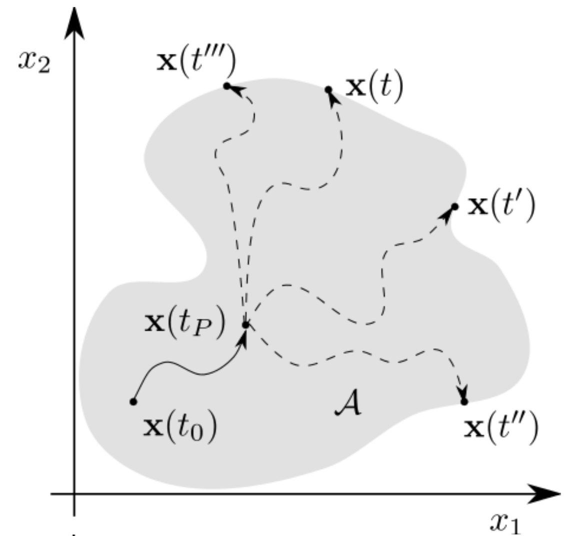


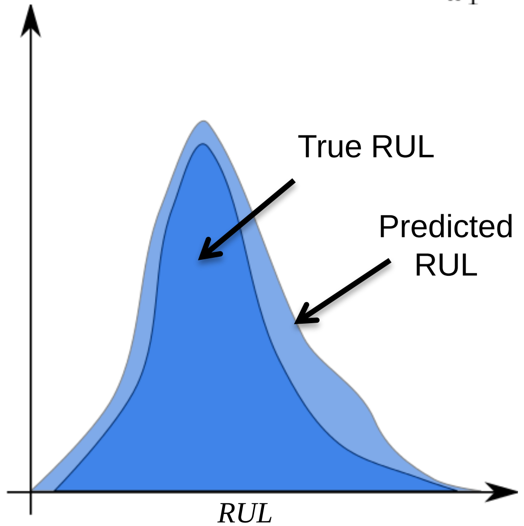
$$\mathcal{A} = \{(\mathbf{x}(t), \boldsymbol{\theta}(t)) : T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 0\}$$

Source: Matthew Daigle, Abhinav Saxena, Kai Goebel, "An Efficient Deterministic Approach to Model-based Prediction Uncertainty Estimation", Annual Conference of the PHM Society 2012, Minneapolis MN

Prediction Uncertainty

- System takes some path *out of many possible paths* until EOL
  - System evolution is a random process, so EOL and RUL are random variables
  - Random due to process noise and uncertain future inputs
  - This uncertainty is *inherent to the system*
- Goal of prognostics algorithm is to predict true distribution of EOL/RUL
  - A misrepresentation of true uncertainty could be disastrous when used for decision-making
- Prognostics algorithm itself adds additional uncertainty
  - For estimation: system state not known exactly, model not known exactly, sensor noise, initial state not known exactly
  - For prediction: model not known exactly, process noise representation not known exactly, future input distribution not known exactly
  - So typically, predicted EOL/RUL distribution wider than true





Inputs for Battery Prognostics

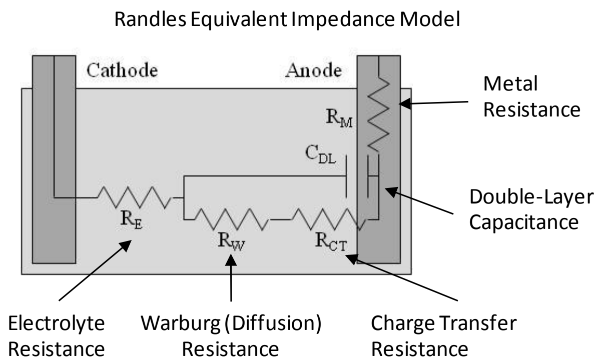
- Real-time models of battery behavior
  - Model of battery discharge
  - Models of battery degradation
  - Models of battery faults
- Access to C, V, & T measurement data
- Characterization of uncertainties
- A prediction algorithm

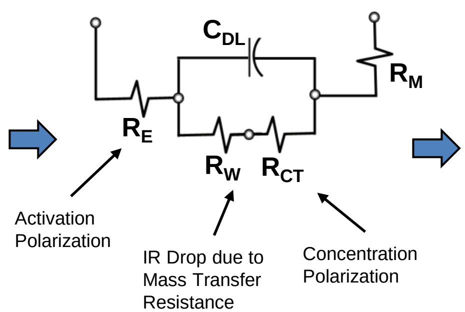
Prognostics

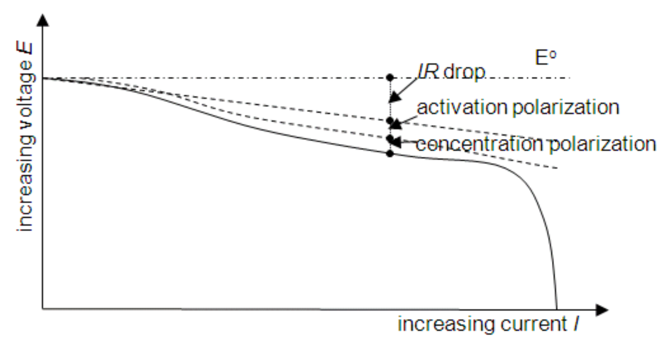
BATTERY MODELING

Li-ion Battery Modeling for Prognostics

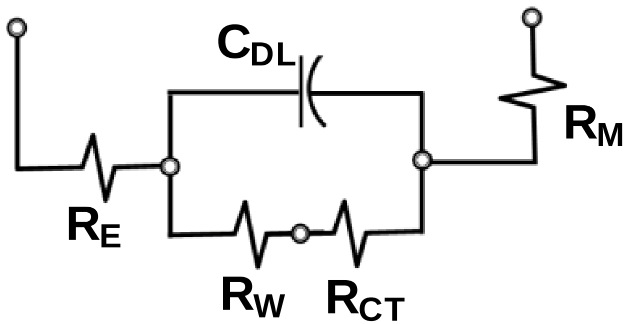
- Intent
  - Develop low to medium fidelity cell level models
    - Nominal degradation models
      - SOC and SOV models
      - SOL models with effects of rest periods
    - Fault models
      - Model faster capacity degradation due to internal faults
      - Characterize fault effects from EIS measurement data
  - Extend models to battery level
    - Hardware simulation testbed to collect measurements from a variety of cell configurations
    - Model effects of temperature and usage history





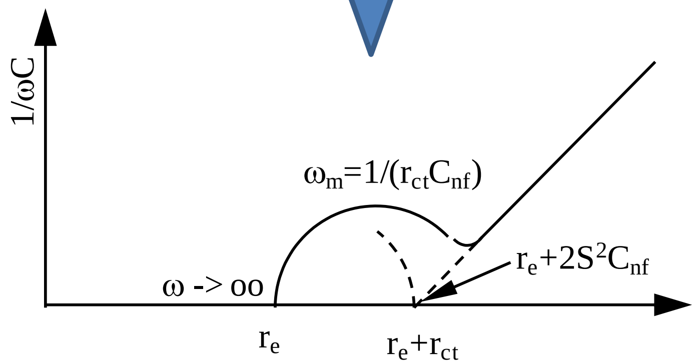


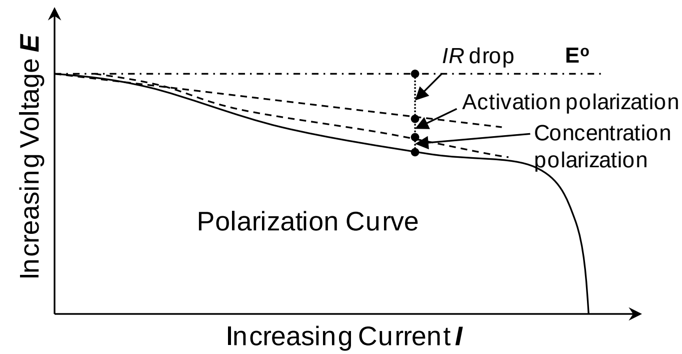
Modeling Approaches

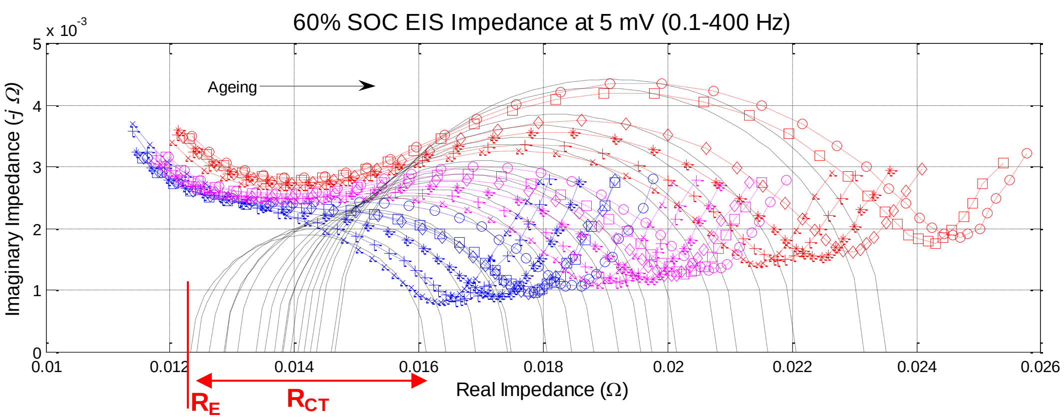


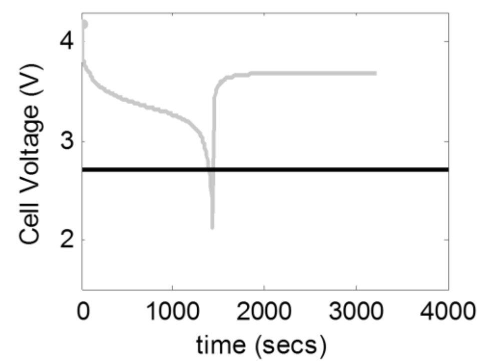
Frequency Domain

Time Domain









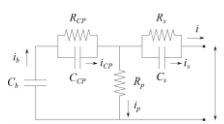
ARC Battery Health Modeling Overview

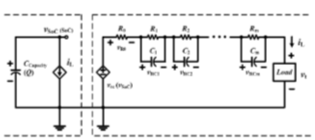
BHM

SoC
Quantifies Remaining Charge in a Discharge cycle

Charge Depletion
Predict End of Discharge (EoD)

- EIS
- In-situ monitoring
  - SoC





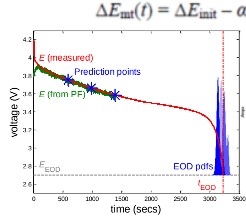
  - SoV

AeroConf'12 AIAA'11, IJPHM'11

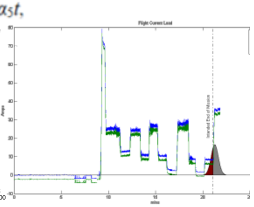
Lumped Parameter – Parameter Estimation via PF
Currents , Voltage and Temperature Measurements

PCoE Dataset Edge 540 dataset

$$E = E^{o} - I(R_E + R_{CT} + R_W).$$
$$E(t) = E^{o} - \Delta E_{sd}(t) - \Delta E_{rd}(t) - \Delta E_{mt}(t),$$
$$\Delta E_{sd}(t) = \alpha_1 \exp(-\alpha_2/t),$$
$$\Delta E_{rd}(t) = \alpha_3 \exp(\alpha_4 t),$$
$$\Delta E_{mt}(t) = \Delta E_{init} - \alpha_5 t,$$



Li-ion Cell



Li-ion Polymer Pack

Faults

SoL
Quantifies Battery Capacity Decay

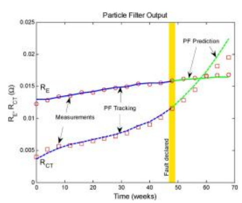
Capacity Decay
Predict End of Life (EoL)

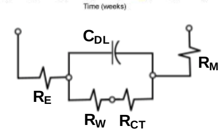
- EIS

Autotestcon'07, AAAI'07, AeroConf'08, I&M'08, IEEE Transactions'09, TIM2009

Lumped Parameter – EIS Measurements Regression

INL Dataset





- In-situ Monitoring

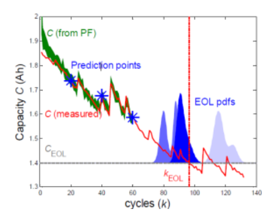
PHM'09

Emperical Model – Coulombic Efficiency + Exponential Recharge Parameter estimation via PF

PCoE Dataset

State transition model $\equiv$
$$\beta_{j,k+1} = \beta_{j,k} + \varphi_{j,k}, \; j = 1,2,$$
$$C_{k+1} = \eta_C \, C_k + \beta_{1,k} \exp(-\beta_{2,k}/\Delta t_k) + \varphi_k$$

Measurement model $\equiv \tilde{C}_k = C_k + \psi_k,$



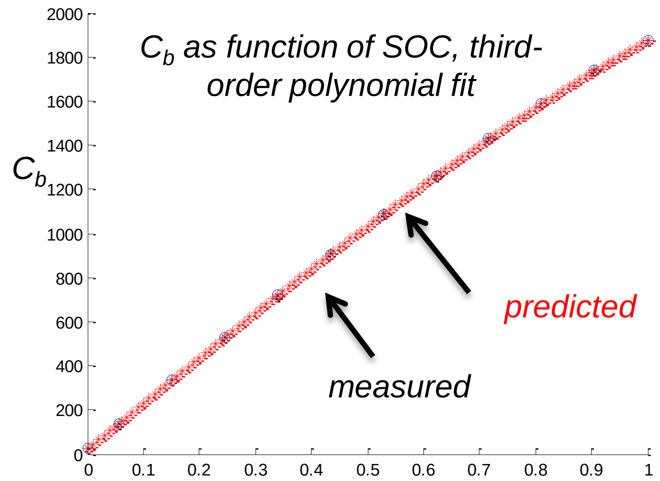
Faults

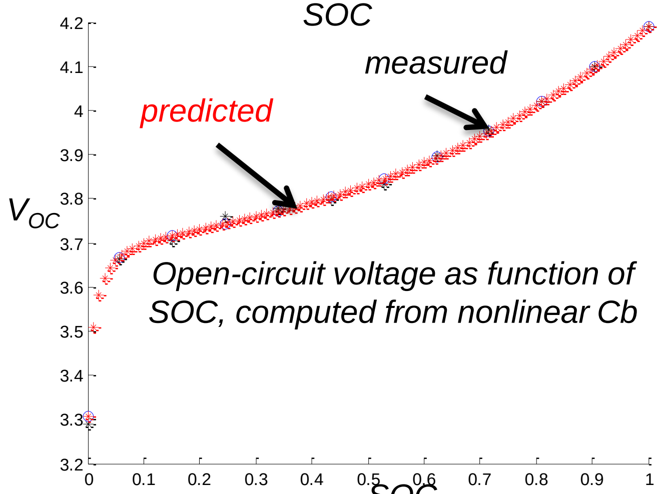
- EIS

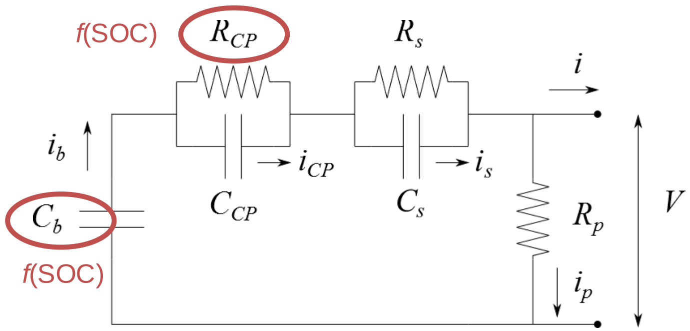
Plate Sulphation
Recrystalization
Passivation
Corrosion
Bridging – Micro-shorts
Dry out
Softening
Mechanical failures

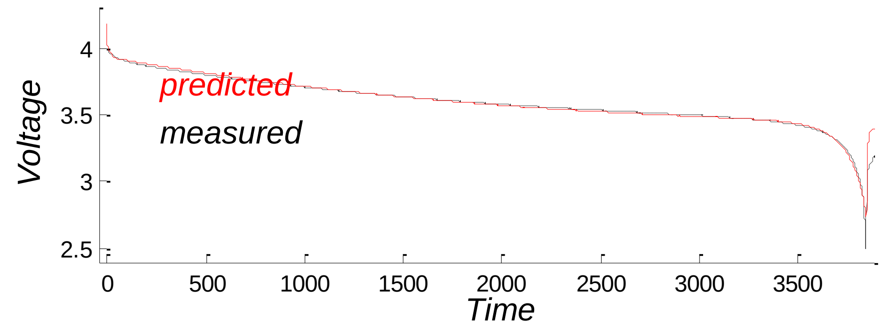
Battery Model Example 1

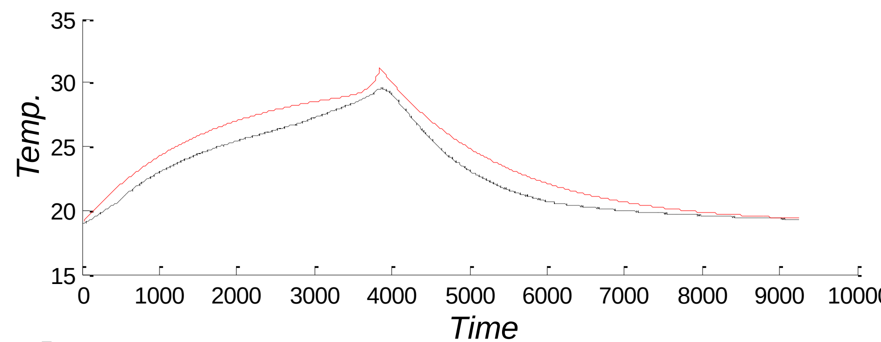
- Developed dynamic battery models for end-of-discharge prediction
- Used electrical circuit equivalent and explored various levels of granularity











Battery Modeling Example 1

- State of charge

$$SOC = 1 - \frac{q_{max} - q_b}{C_{max}}$$

- CP resistance

$$R_{CP} = R_{CP0} + R_{CP1} \exp R_{CP2}(1 - SOC).$$

- Voltages

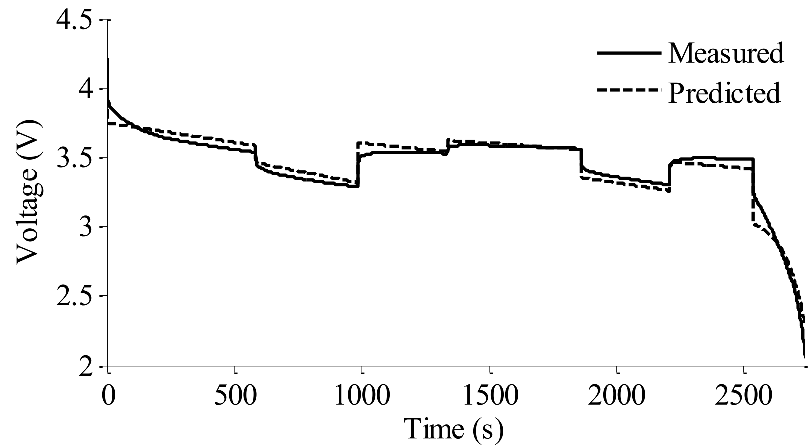
$$V = V_b - V_{CP} - V_s.$$

$$\begin{aligned} V_b &= q_b/C_b \\ V_{CP} &= q_{CP}/C_{CP} \\ V_s &= q_s/C_s \\ V_p &= V_b - V_{CP}. \end{aligned}$$

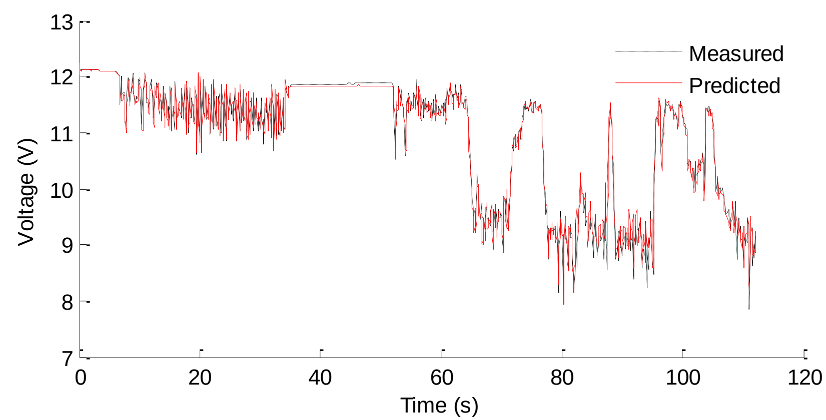
- Currents and Charges

$$\begin{aligned} i_p &= V_p/R_p \\ i_b &= i_p + i \\ i_{CP} &= i_b - V_{CP}/R_{CP} \\ i_s &= i - V_s/R_s, \end{aligned}$$

$$\begin{aligned} \dot{q}_b &= -i_b \\ \dot{q}_{CP} &= i_{CP} \\ \dot{q}_s &= i_s. \end{aligned}$$

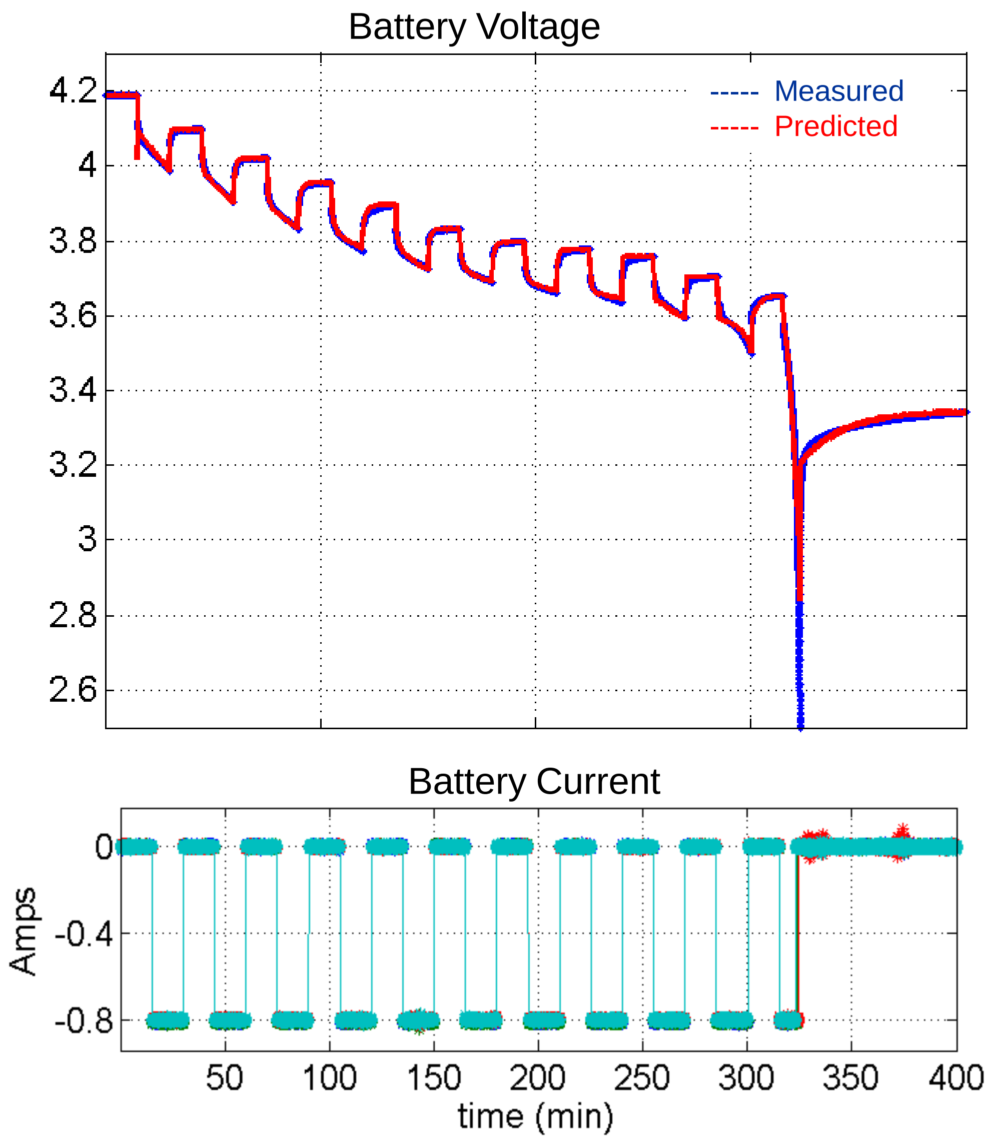


Comparison with testbed data



Comparison with rover battery data

Circuit Model with Single RC Branch



PREDICTION

End of Discharge (EOD) Prediction

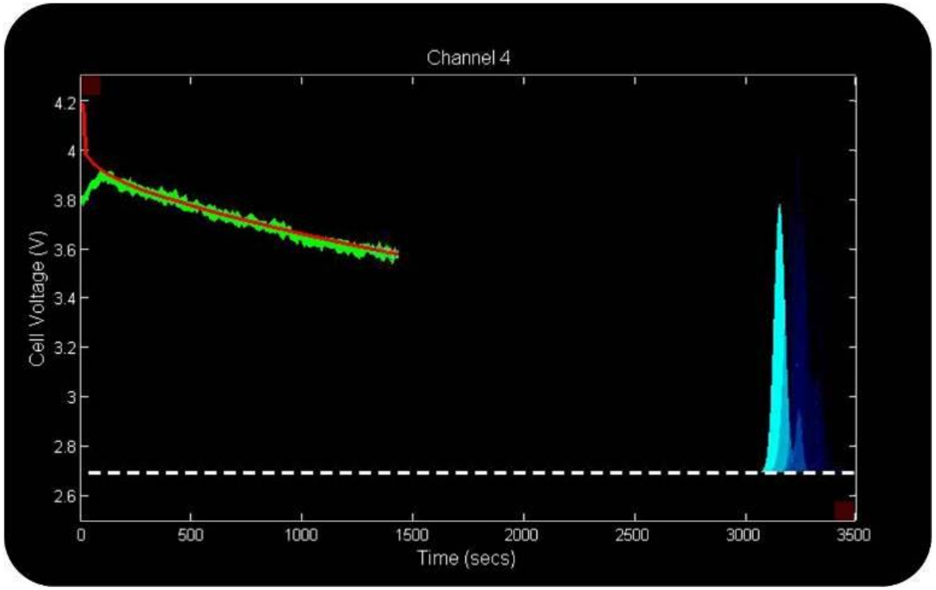
- Select discharge model
- Identify discharge model parameters and learn parameters from testbed data
- Initialize the Bayesian Framework with identified model to track discharge realtime and fine tune model parameters
- Characterize uncertainties and estimate future loads
- Use the refined model to predict end of charge

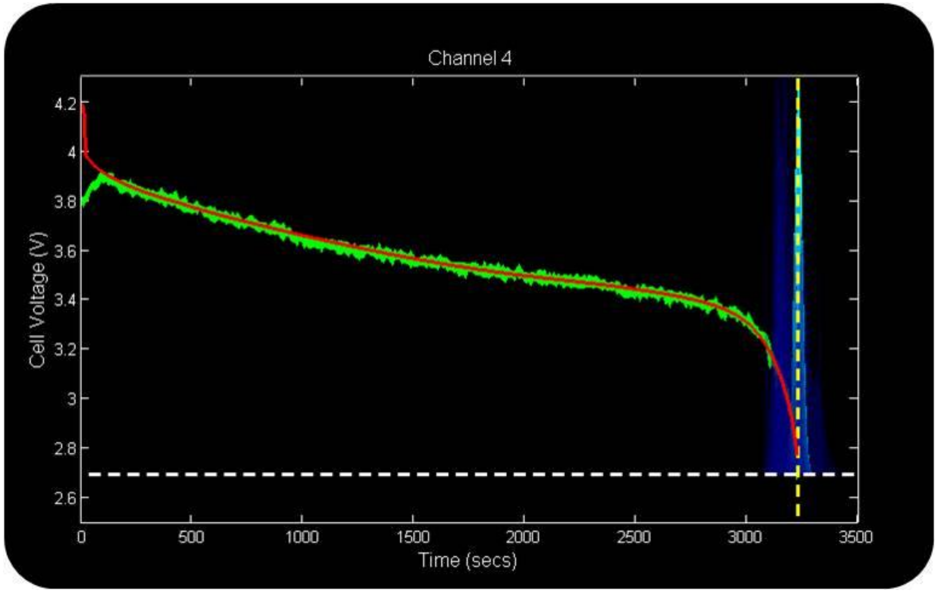
Bayesian Frameworks utilized for prediction

- Particle Filters
- Kalman Filter and variants – EKF, UKF, etc.

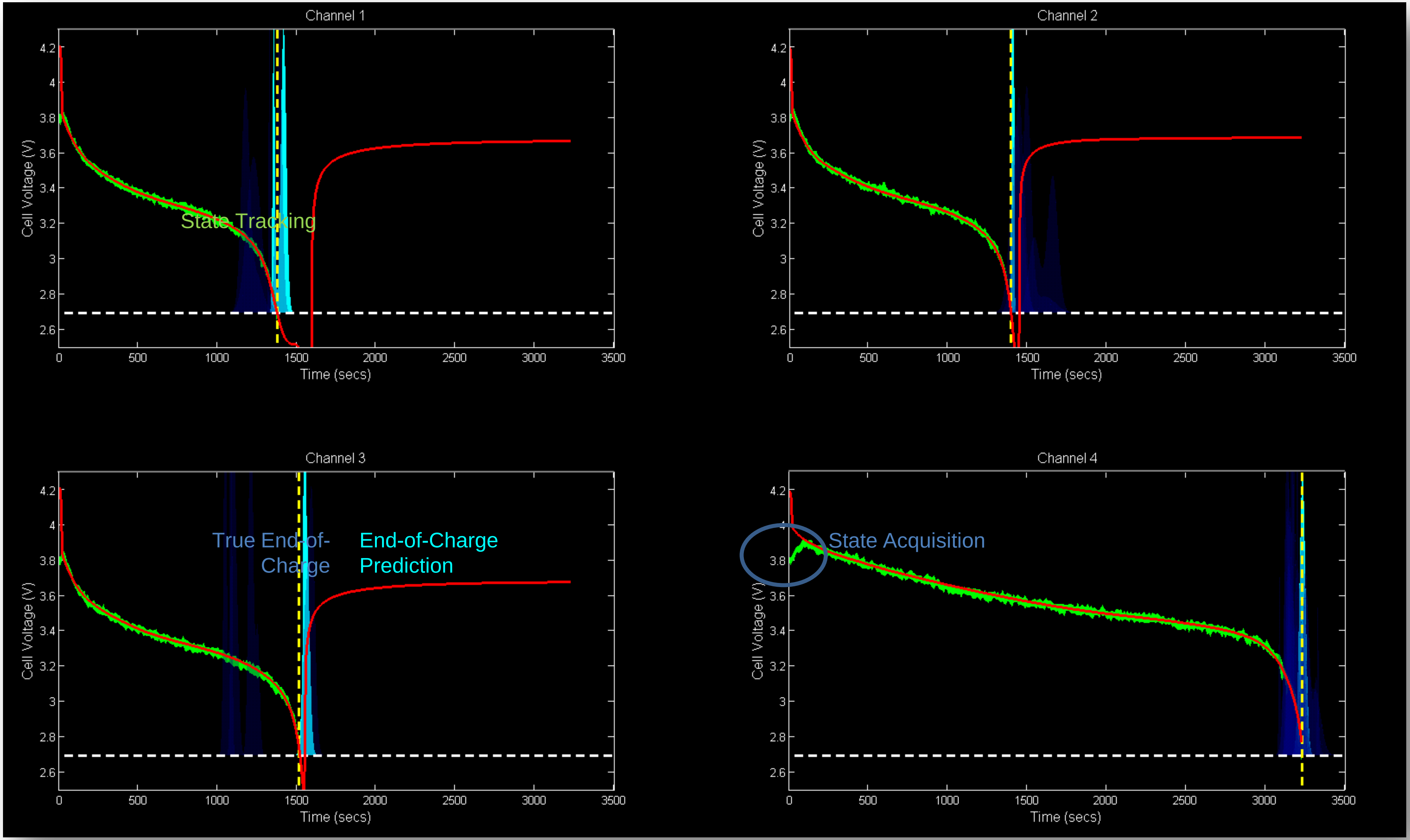
Prognostics Validation

- Prognostics Lab Li-ion battery Demo
- Predictions start early on as model parameters get tuned
- Predictions update on a regular basis as more information becomes available
- Predictions are represented as a pdf of expected End-of-Life (failure) time
- Underlying physics based model is predict the non-linear behavior
- Once tested on lab testbed, algorithms are tested onboard a UAV flight for validation





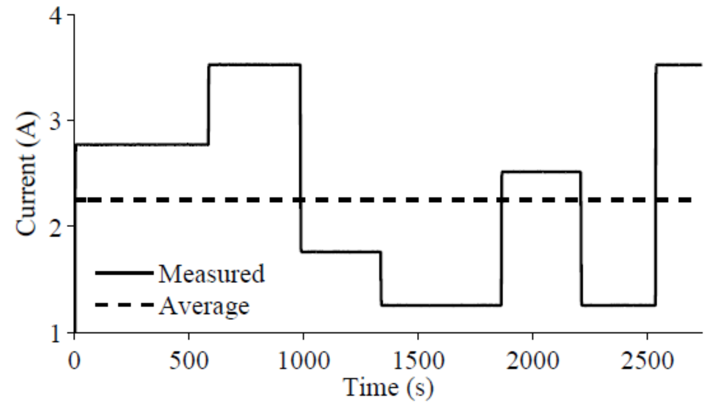
Results: EOD Prediction

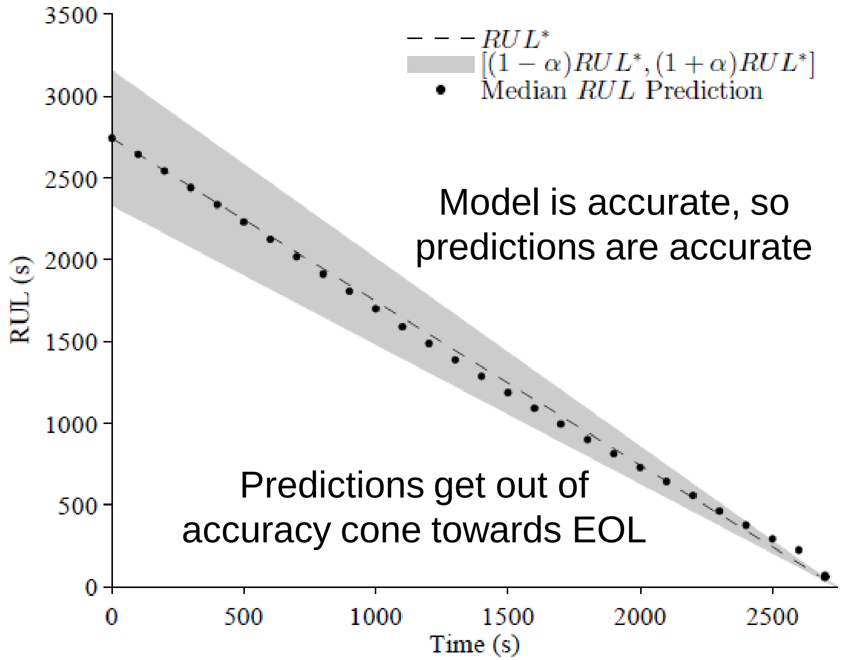


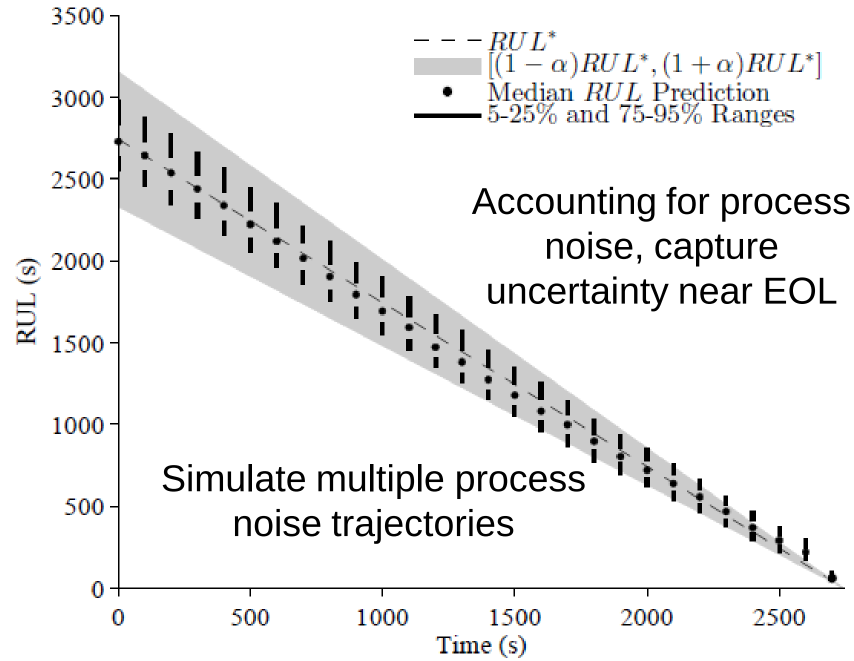
Narrower pdfs → better precision

Experimental Results: Known Inputs

- Input is the current drawn from the battery
- First, assume future inputs are known
- Here, process noise included to account for model uncertainty





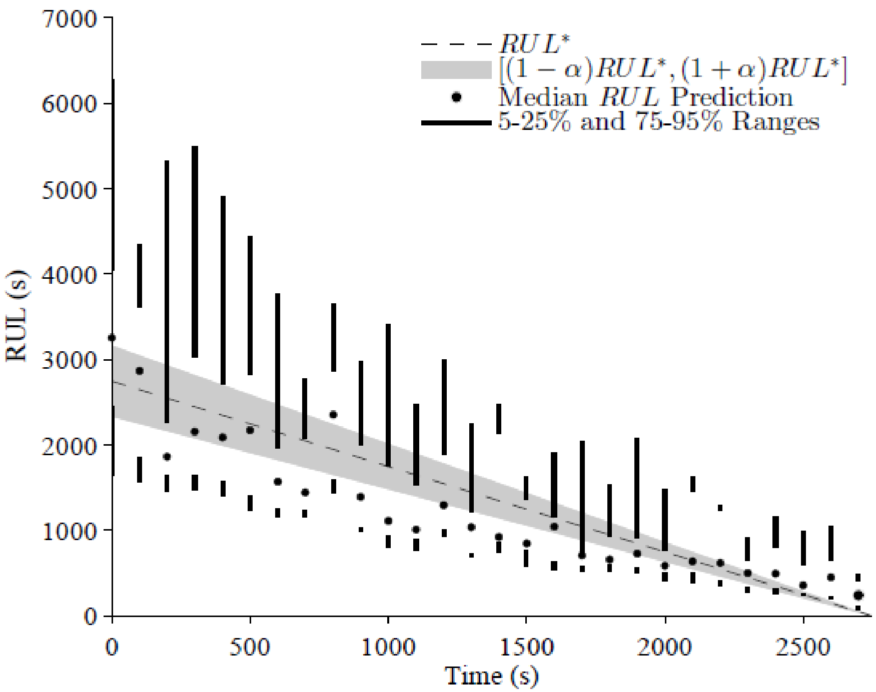


Source: Matthew Daigle, Abhinav Saxena, Kai Goebel, "An Efficient Deterministic Approach to Model-based Prediction Uncertainty Estimation", Annual Conference of the PHM Society 2012, Minneapolis MN

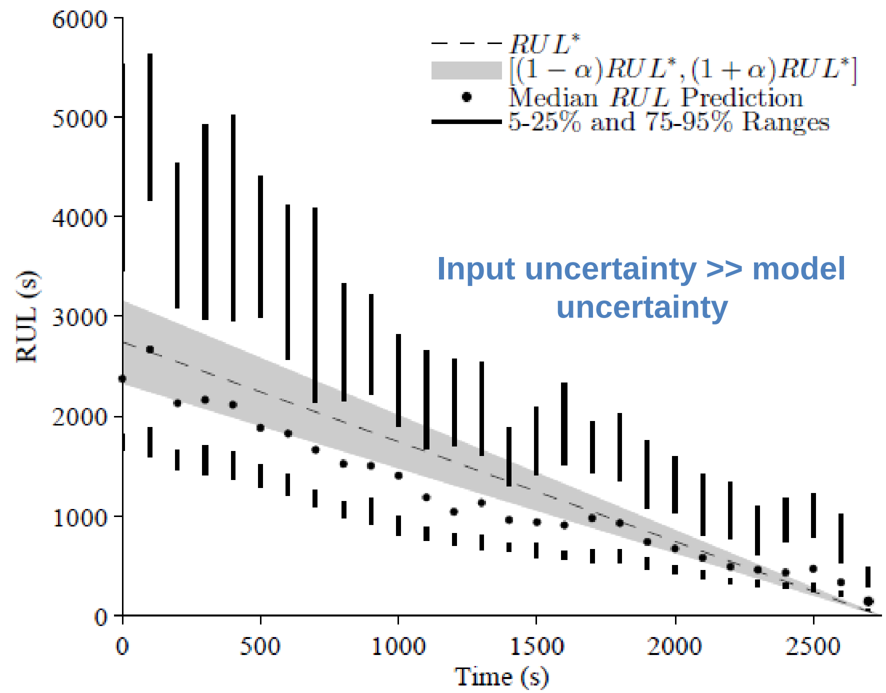
Experimental Results: Unknown Inputs

- Assume future inputs are unknown
- Assume constant discharge drawn from uniform distribution from 1 to 4 A
- Sample randomly from this distribution at each prediction point

10 samples



100 samples



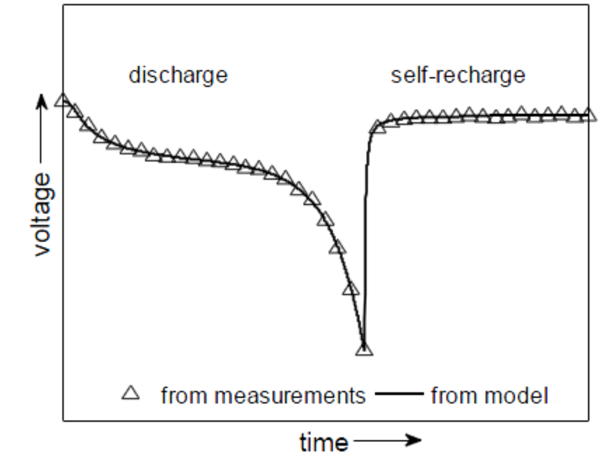
Source: Matthew Daigle, Abhinav Saxena, Kai Goebel, “An Efficient Deterministic Approach to Model-based Prediction Uncertainty Estimation”, Annual Conference of the PHM Society 2012, Minneapolis MN

Modeling SOL

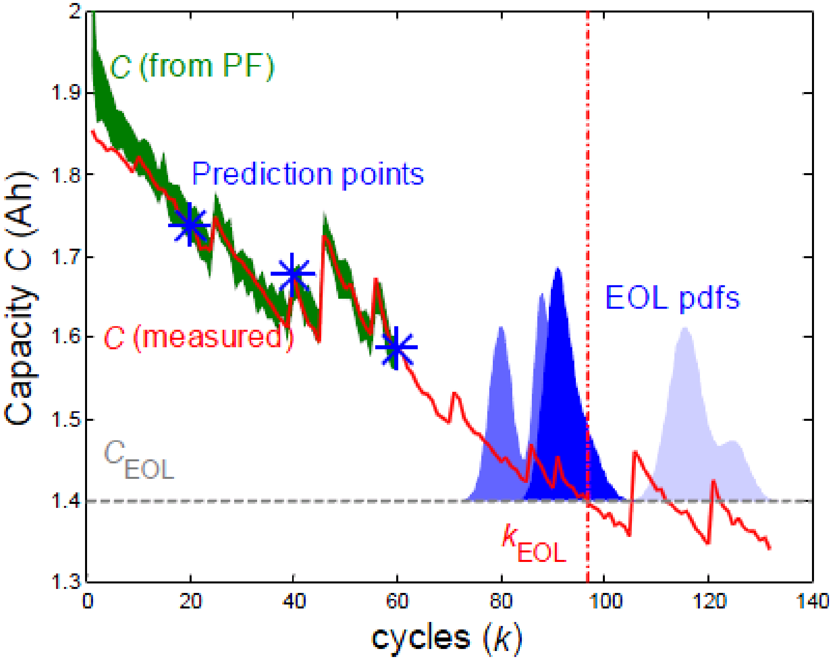
State transition model $\equiv$

$$\beta_{j,k+1} = \beta_{j,k} + \varphi_{j,k}\,,\ j = 1,2,$$
$$C_{k+1} = \eta_C\, C_k + \beta_{1,k} \exp(-\beta_{2,k} / \Delta t_k) + \varphi_k\,,$$

Measurement model $\equiv\ \tilde{C}_k = C_k + \psi_k\,,$

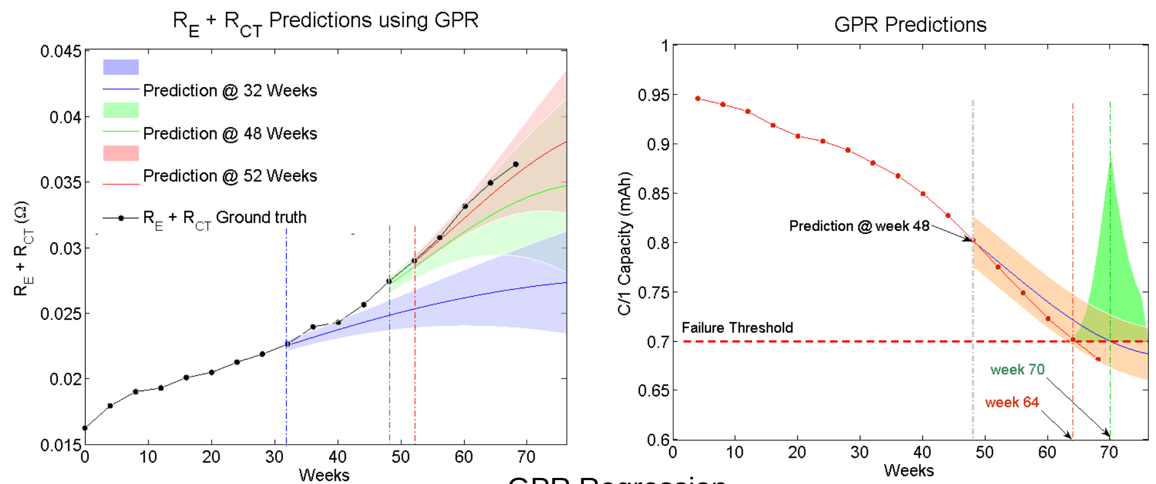


- A simple model based on
  - Coulombic efficiency
    - Ratio of prior charge capacity available during discharge
    - Coulombic efficiency determines how capacity decays in the next cycle
  - Rest periods help regain some charge
    - An exponential model for recharge during rest periods
- Estimate parameters β_j using PF

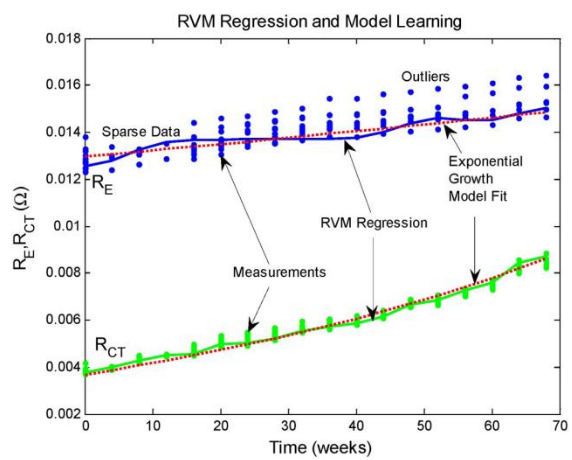


Source: Saha, B., Goebel, K., 'Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework', Annual Conference of the PHM Society (PHM09), 2009, San Diego CA

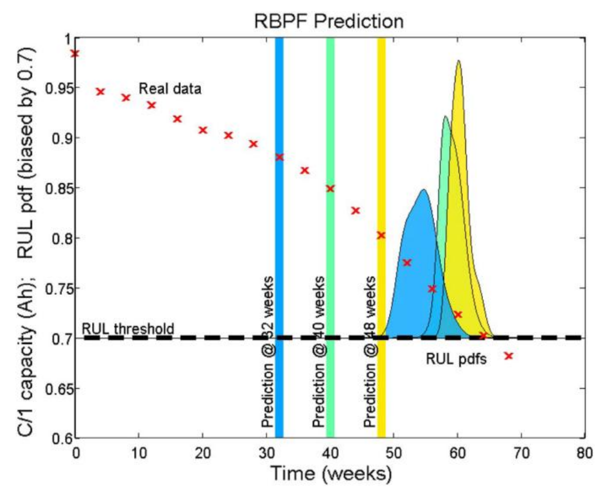
Frequency Domain Data Models



GPR Regression



RVM Regression



Filtering

Sources:

Goebel, K., Saha, B., Saxena, A., Celaya, J. R. , Christopherson, J. P., "Prognostics in Battery Health Management", IEEE Instrumentation and Measurement Magazine, Vol. 11(4), pp. 33-40, August 2008.

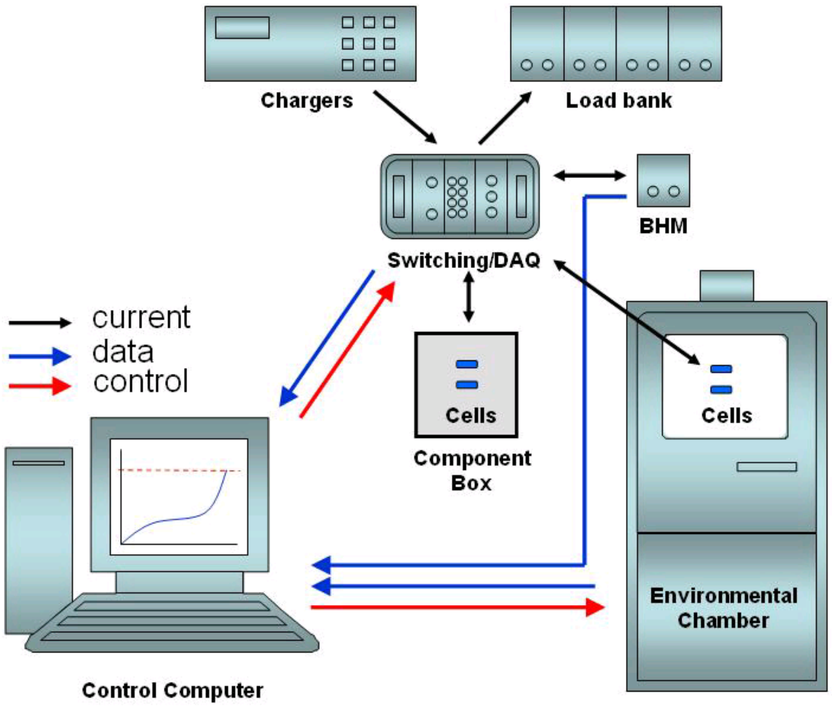
Saha, B., and Goebel, K., “Uncertainty Management for Diagnostics and Prognostics of Batteries using Bayesian Techniques”, Proceedings of the IEEE Aerospace Conference, BigSky MT, 2008.

Aging

EXPERIMENTS

Current Battery Testbed

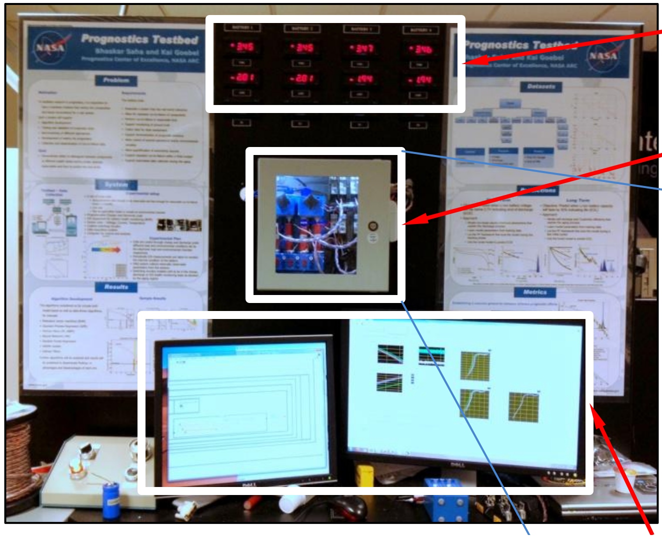
- Four cells are cycled simultaneously
  - charge and discharge under different load and environmental conditions set by the electronic load and environmental chamber respectively
- Periodically EIS measurements
  - to monitor the internal condition of the battery
- DAQ system collects externally observable parameters from the sensors
  - C, V, and T data
- Switching circuitry
  - enables cells to be in the charge, discharge or EIS health monitoring state as dictated by the aging regime



Processes	Predict
• Charge • Discharge • Recovery from rest	• End of charge • End of life

EIS: Electro-chemical Impedance Spectroscopy

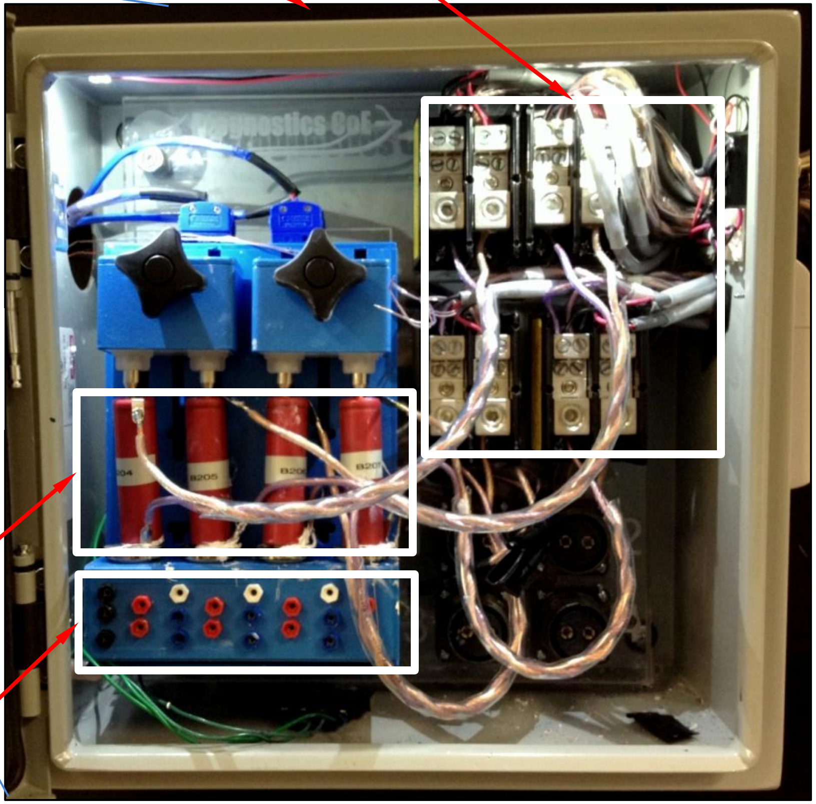
Current Testbed at ARC



Measurement Display

Current, Voltage, and Temperature Measurement

Battery Aging and Measurement Cell



Aging Software and Measurement GUI

EIS Box

4 Channel Programmable Load

Cells under test

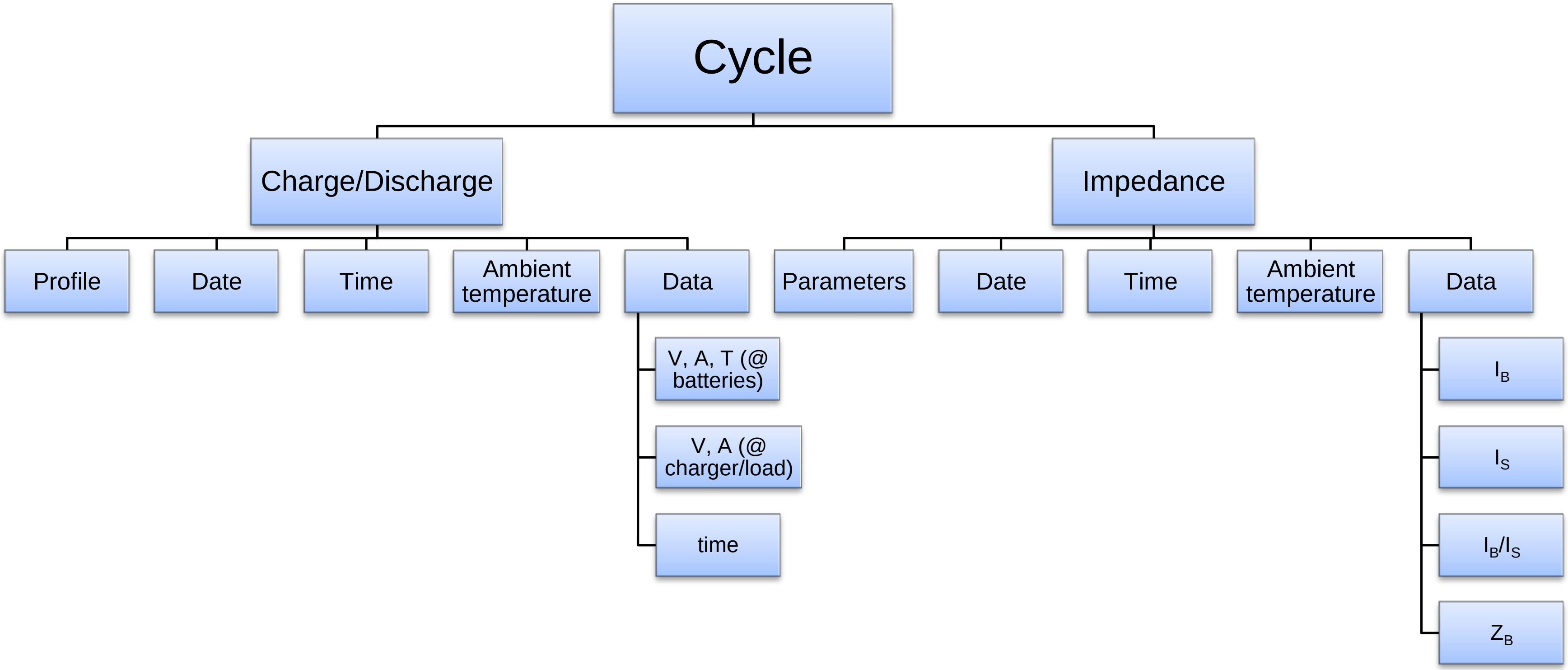
Four Point EIS Measurement

Programmable Power Supplies

New Testbed

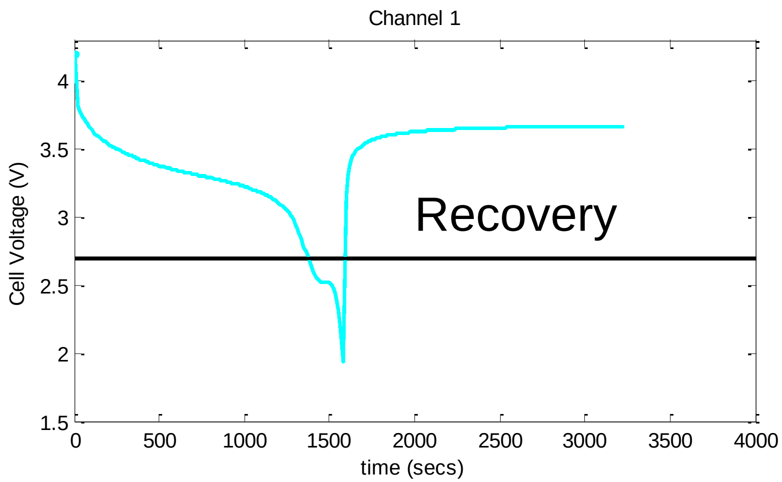
- Improved throughput and capability
  - 32 Channels
    - 5A, 10 V
  - 3 Channels
    - 50A, 100V
  - Automated EIS measurements
    - 1mHz – 30KHz
  - Automated thermal profiling
- Battery Simulator
  - To simulate a pack with different cell configurations

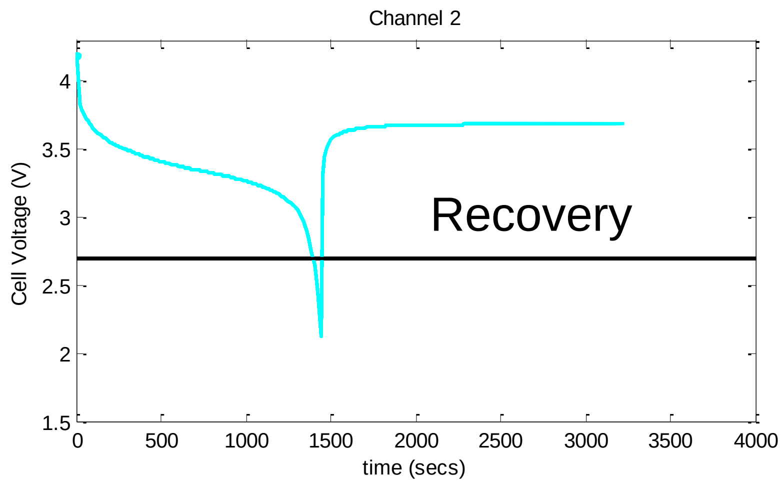
Data Format

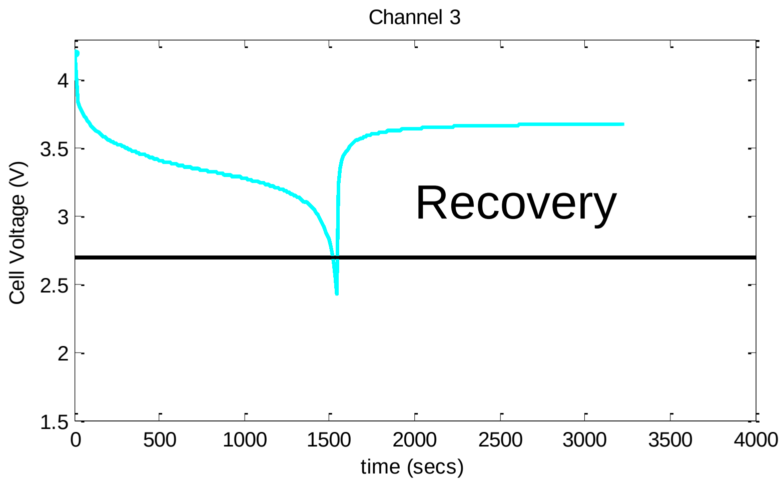


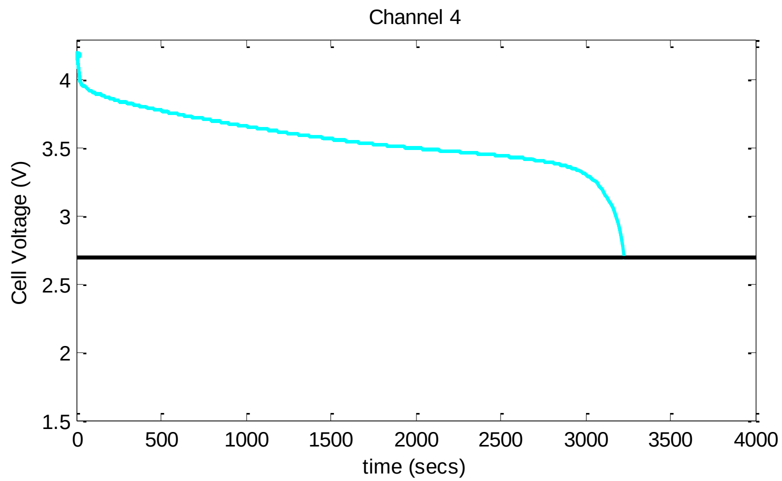
Datasets publically available at http://ti.arc.nasa.gov/project/prognostic-data-repository (>7,000 downloads till date)

Discharge Cycle Data

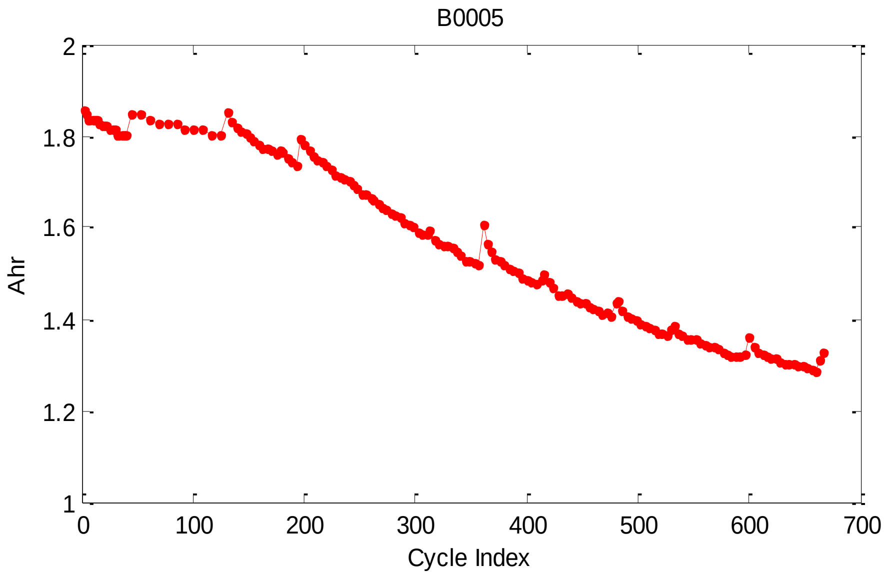


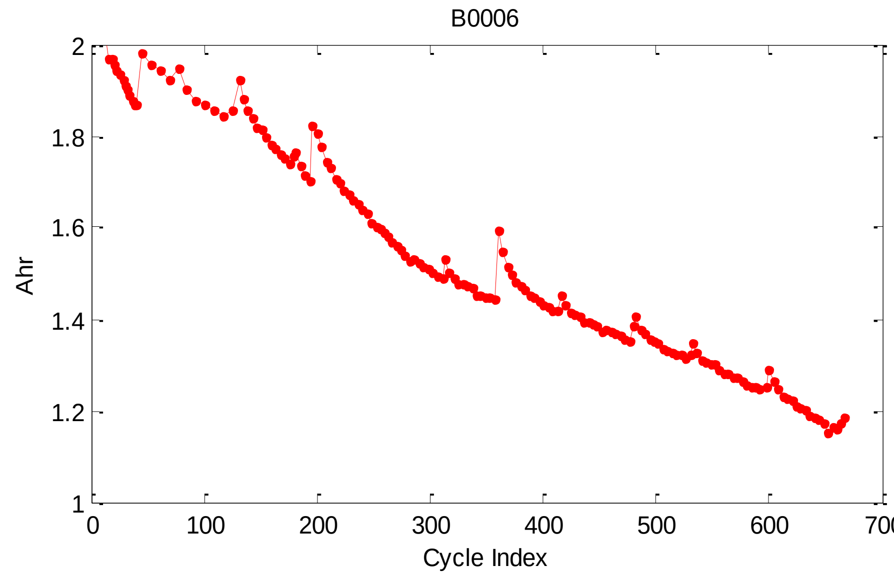


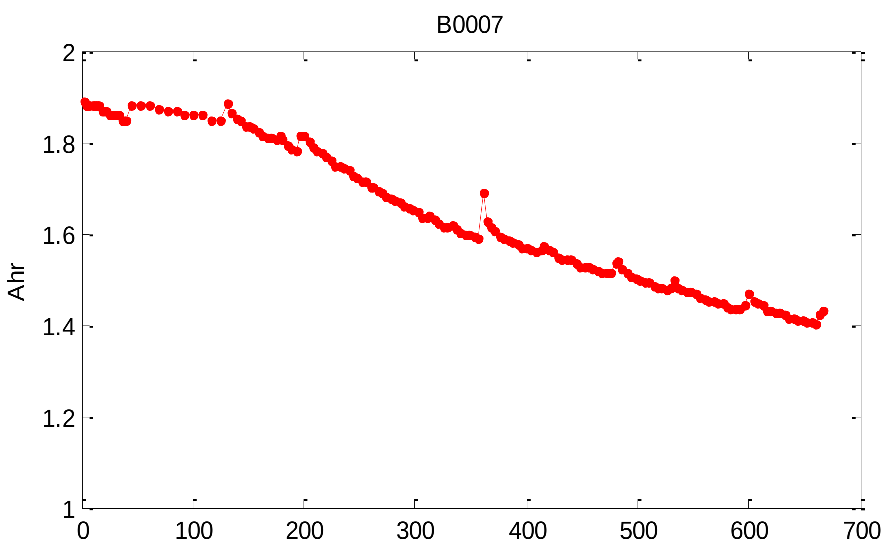


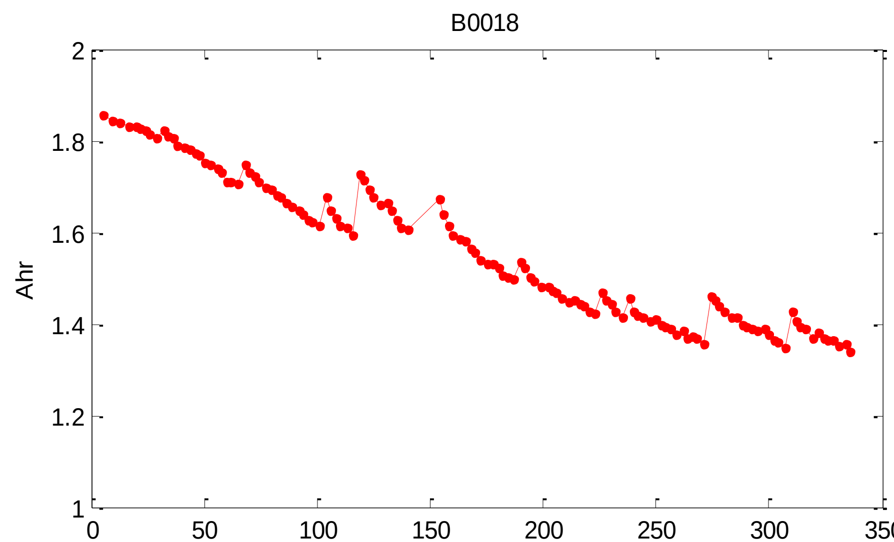


Run-to-Failure Data









Experiments Test Matrix

- Characterize
  - Effects of load
  - Effects of temperature
  - Combined effects
  - Effects of transients during load switching

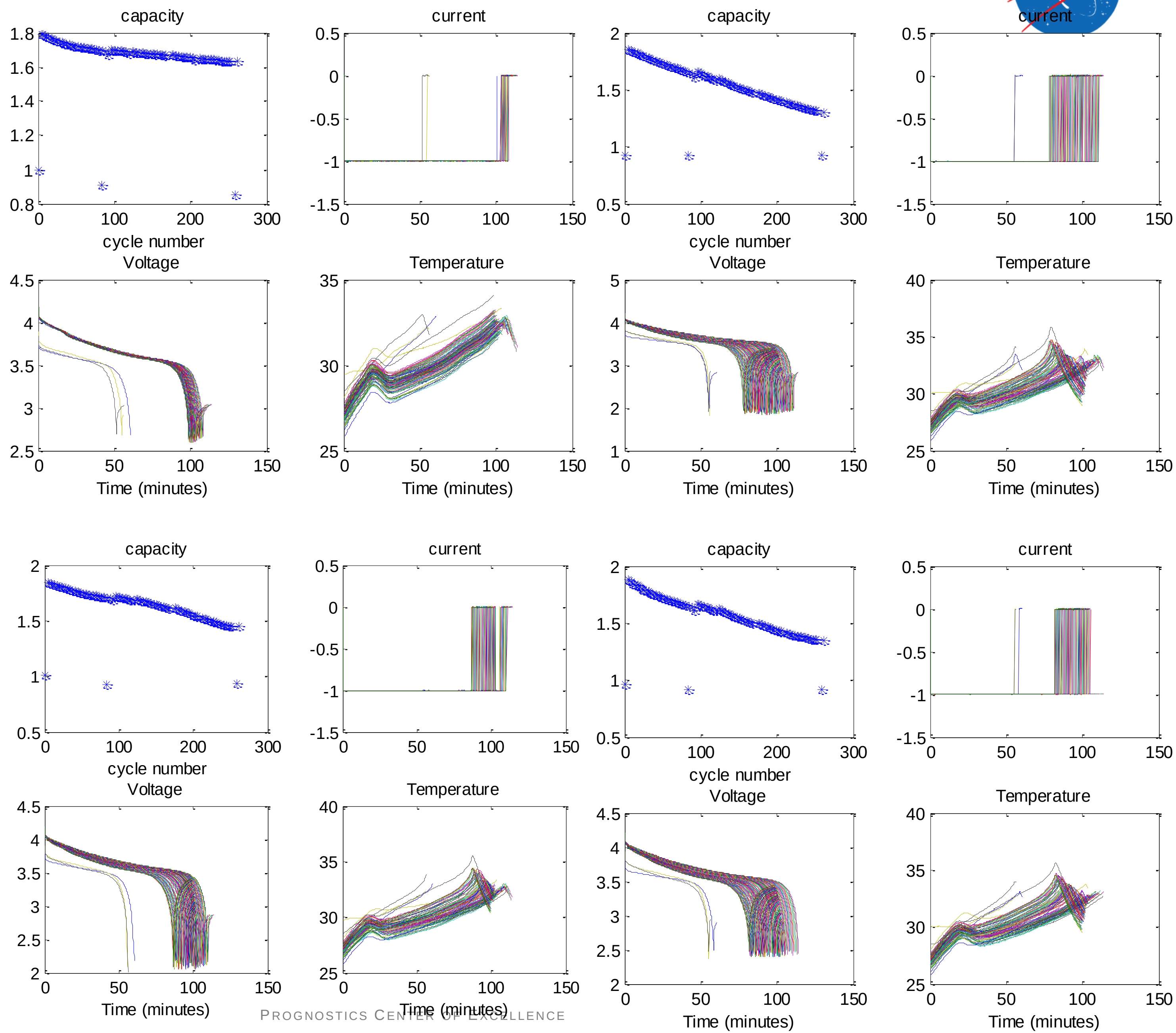
Battery Test Matrix				
	4 deg C	24 deg C	44 deg C	24 & 44 deg C
Fixed 1A	45, 46, 47, 48	57,58,59,60		
Fixed 2A	49, 50, 51, 52, 53, 54, 55, 56	5, 6, 7, 18, 36		
Fixed 4A	70,71	21, 22, 23, 33, 34,72,73	29, 30, 31, 32	
Fixed 4A, 2A, 1A	41, 42, 43, 44			38, 39, 40
Variable 0A and 4A		25, 26, 27, 28		
Variable 1A, 2A, 4A				

Fixed 1A discharge, 1.5A charge at 24deg C   Batteries: 57, 58, 59, 60

Observations

Batteries all start at about 1.8Ah and are degraded to various degrees over about 280 Cycles

Results look very consistent

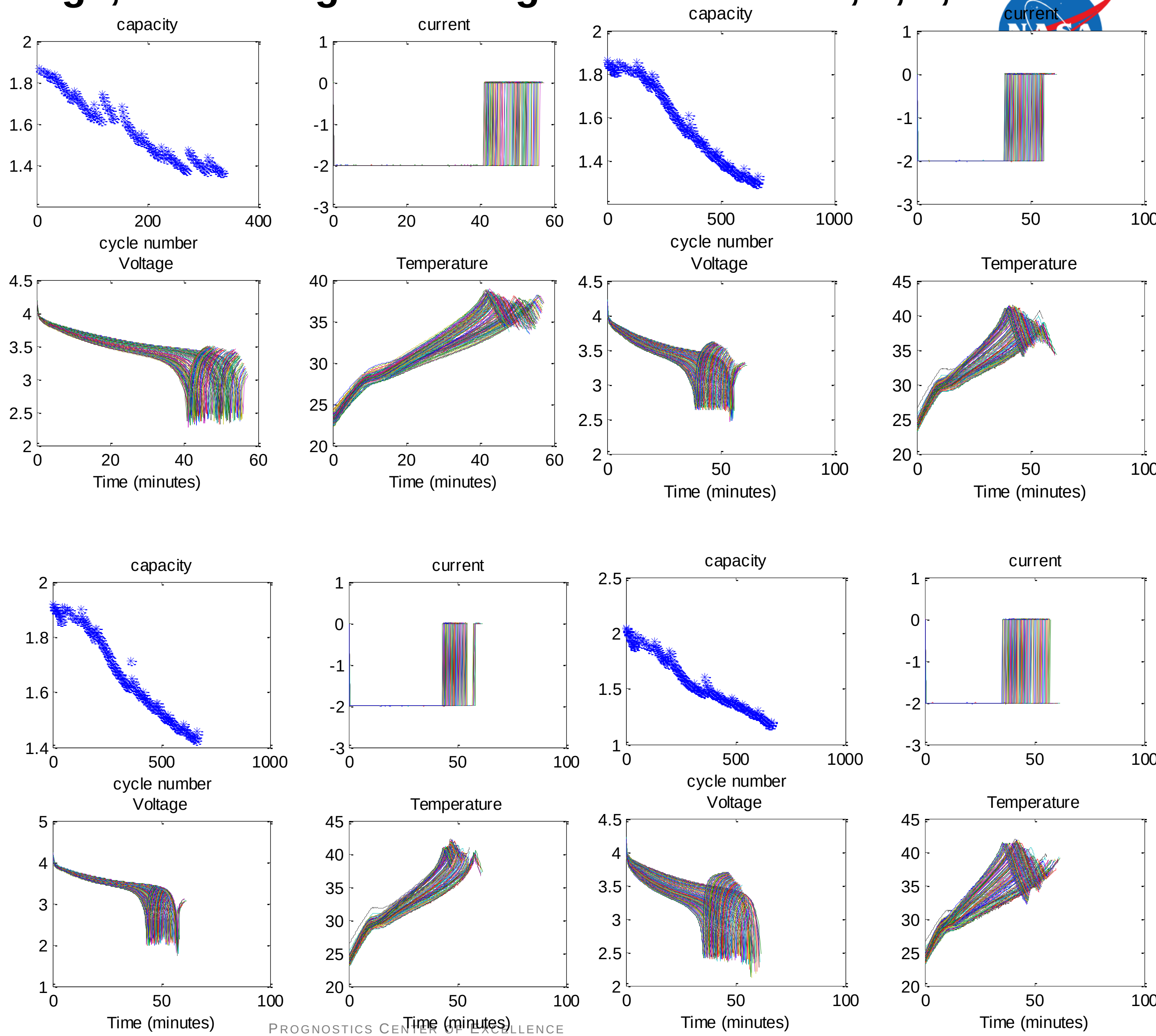


Fixed 2A discharge, 1.5A charge at 24deg C   Batteries: 5, 6, 7, 18

Observations

Batteries all start at about 1.8Ah and 2Ah

The results look fairly consistent and show EOL at about 500 cycles



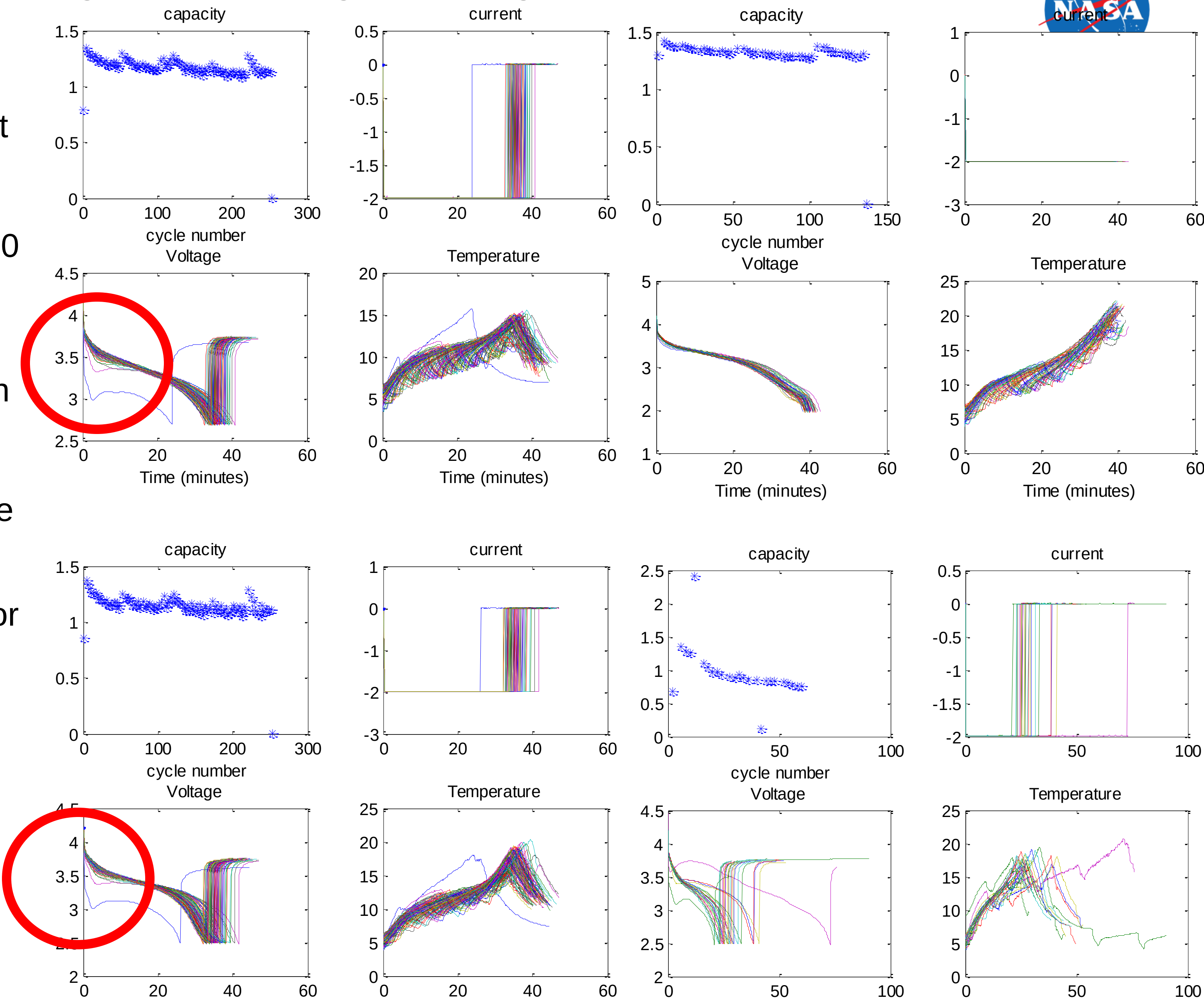
Fixed 2A discharge, 1.5A charge at 4deg C   Batteries: 49, 53, 55, 56

Observations

Batteries all start at about 1.4Ah and show little degradation over 60 - 250 Cycles

Results look consistent although cycle times are varied and some battery results were thrown out

Double dip behavior in some cycles



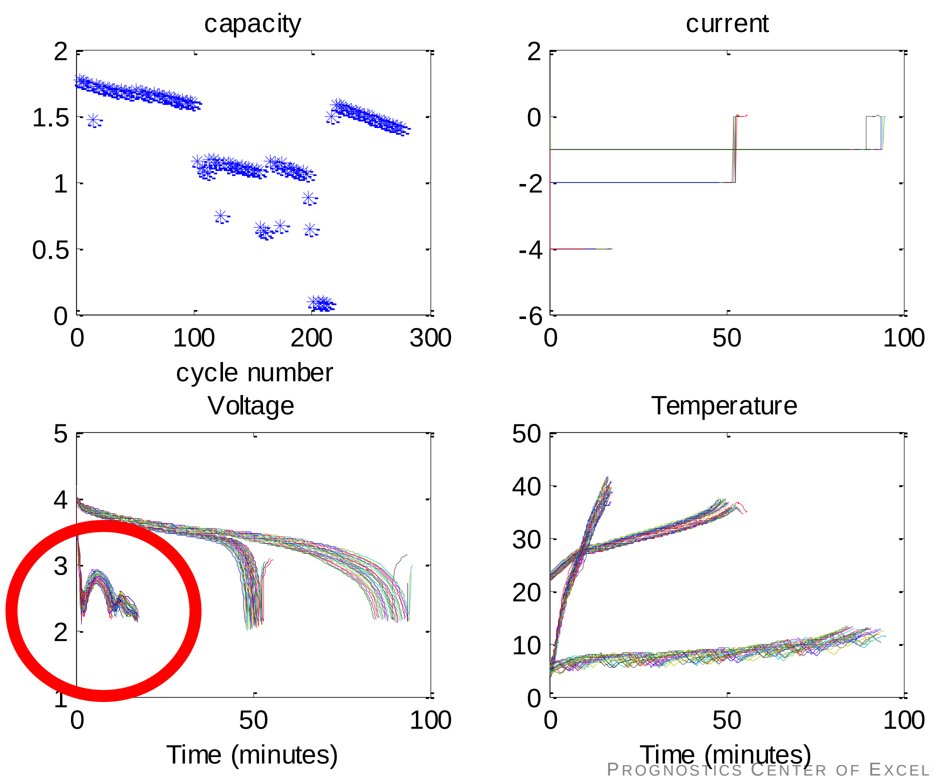
Cycles at 1A, 2A, 4A discharge, 1.5A charge at 4deg C
Batteries: 41,42,43,44

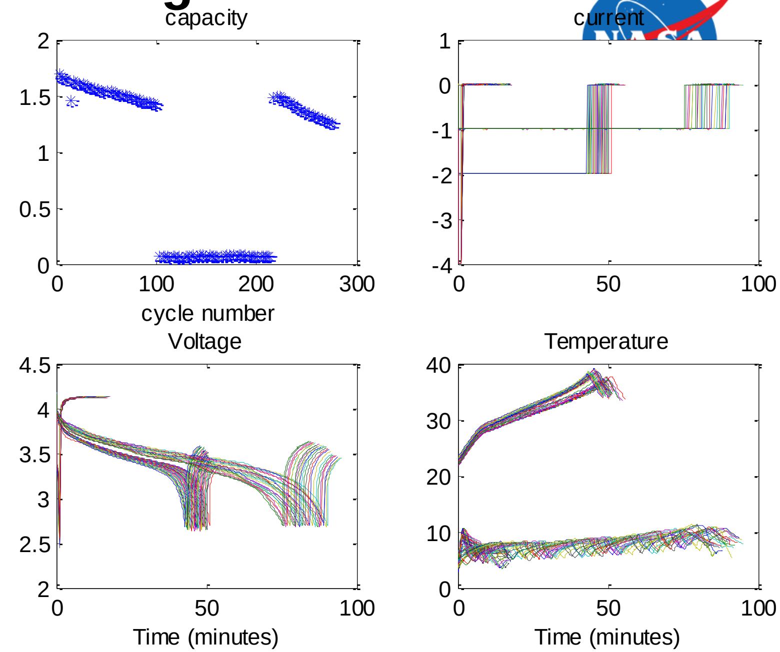
Observations

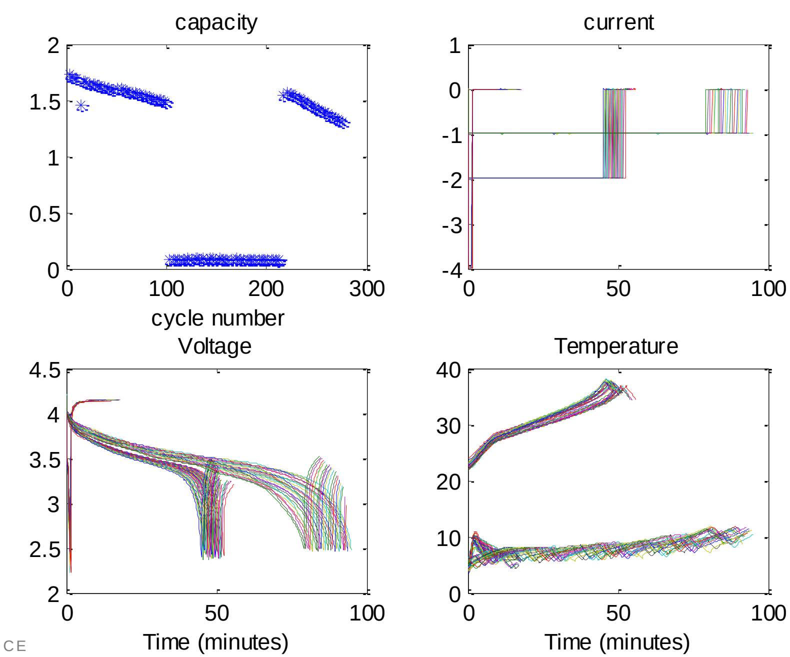
Batteries are initially started at room temperature and 2A discharge

Then the batteries are cycled at 4A and 1A

One of the batteries shows the double dip / triple dip behavior







Preliminary Observations

FAULT INJECTION EXPERIMENTS

In collaboration with NASA GRC and inputs from JSC

Fault Injection Plan and Rationale

- Most failures in Li-ion batteries are caused by Li-plating on the electrodes
  - There are several root causes and associated mechanisms that lead to Li-plating
  - All causes ultimately lead to Li-plating, followed by internal shorts due to dendrite formation, and finally resulting in thermal runaway
- There are several methods to induce Li-plating to inject internal faults
  - Overcharge – can be very dangerous and generally not recommended without appropriate safety arrangements
    - This was tried and significant fade in capacity was observed but experiments halted due to dangerous conditions
    - Cells were stored for detailed EIS measurements to confirm the damage
  - Deep discharge – less dangerous but requires to find a very delicate balance between not stressing the cell enough and damaging the cell instantly
    - This was tried but with limited success as the conditions used were perhaps not stressful enough to visibly show extra degradation
    - Experiments took very long time, had to discontinue when the decision to switch back to 18650 cells was made
  - High temperature high C-rate charging/discharging – this is relatively dangerous if not controlled properly and can lead to thermal runaway
    - No recommended due to safety concerns
    - High temperatures case some irreversible chemical reactions that can lead to volatile gas emissions causing explosions [6]
    - We may try some once thermal chamber becomes available and integrated with our testbed

Fault Injection Plan

- Low temperature high C-rate charging/discharging – relatively safe and effective
  - Haven't been able to try yet as our test stand is currently not capable of high C-rate charging and that is where the most damage is expected
  - A study on role of operational temperatures on battery performance showed that low temperature charging resulted in Li-plating and a faster capacity decay. This capacity decay was further worsened with higher C-rates [1,5].
  - Another study confirmed that high discharge rates resulted in higher capacity fades . Capacity fade of 1% took 450cycles at 1C, <50 cycles at 10C, <5cycles at 20C and <1 cycle at 27C. They also show that low temperatures further make the matter worse. [2,8]
  - Several cell types were tested and it was found that in general low temperature and high C-rate discharges result in faster capacity fades due to Li-plating. However, depending on the cell chemistry and design (e.g. high cathode to anode capacity) degree of Li-Plating varies [3]
  - Other references show that cycling at high temperatures reduces the battery life faster. At the same time charging at low temperatures can be damaging through Li-Plating [4, 6-8]
  - With the ongoing upgrades we may be able to carry out such experiments soon

- References

[1] G. Dudley, "ExoMars Rover battery Modeling & Life Tests", NASA Battery Workshop 2010, Huntsville AL

[2] J. Jeevarajan, B. Strangways, T. Nelson, "Performance and Safety Evaluation of High-rate 18650 Lithium IronPhosphate Cells", NASA Battery workshop 2009

[3] *Michelle A. Manzo et. al.* "NASA Aerospace Flight Battery Program", NASA Engineering and safety Center Technical Report, Doc# RP-08-75 V1.0 http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20100027579_2010030201.pdf

[4] Jay Frankhouser etal, "Commercial lithium-ion reserve power systems", Battcon 2010 Conference, Hollywood, FL

[5] M. C. Smart, L. D. Whitcanack and B. V. Ratnakumar, "Safe Charge Rates for Lithium-Ion Cells - Effects of Lithium Plating", NASA battery Workshop 2007, Huntsville AL

[6] http://batteryuniversity.com/learn/article/charging_at_high_and_low_temperatures

[7] G. Gavea, *Y. Borthomieu, B. Lagattu, J.-P. Planchat,* "Evaluation of a low temperature Li-ion cell for space", Acta Astronautica 54 (2004) 559 – 563

[8] Jon S. Read, J. Jeeverajan, P. Patel, J. Bytella, "Performance and Safety Testing of Panasonic 2.9 Ah Li-ion NCR 18650 Cells" NASA Battery workshop 2009

Ongoing and Future Work

- Develop enhanced models at all granularities
- Include effects of temperature
- Automated reconfiguration and re-planning methods for effective BHM
- Battery level extensions
- Fault mode study and modeling

Acknowledgements

NASA ARMD's Aviation Safety Program

NASA Langley Research Center

NASA Glenn Research Center

Member of the Prognostics Center of Excellence (PCoE) at Ames Research Center

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http://prognostics.nasa.gov

THANK YOU !!